Electric Vehicle Urban Exploration by Anti-pheromone Swarm based Algorithms

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Abstract. In this work we show how a simple anti-pheromone ant foraging based algorithm can be effective in urban navigation by reducing exploration times. We use a distributed multi agent architecture to test this algorithm. Swarm collaboration is analysed for different scenarios with varying number of units and map complexity. We show how an increase in the number of robots results in smaller exploration times. Also, we measure how the complexity of the map topology affects the navigability. We validate our approach through numerical tests with both synthetic random generated maps and real bicycle routes in four cities. Also, by monitoring the dynamics of three real prototypes built at the laboratory, we check both the feasibility of our approach and the robustness of the algorithm.

Keywords: Smart Cities, route optimization, swarm intelligence, robots.

1 Introduction

A major challenge in Smart Cities (SC) [1] is the dynamic optimization of routes under different criteria. The objective is to manage a flood of electrical vehicles (EV) efficiently and in a sustainable way. The problem can be solved with different strategies, one of the most common found in literature is the use of a bio-inspired algorithms [2].

In this work we provide an implementation of a well-known bio-inspired meta-heuristic to analyze the collaborative routing of EV in cities. Moreover, we investigate the behavior of a swarm of robots in real environments.

The main difficulty in coordinating a robot swarm lies in the communication among units. In this regard, previous works can be split into implicit/indirect and explicit/direct communication. Implicit communication –also known as *stigmergy*- is based on the context and some of its most typical uses can be found in [3]–[6]. In this regard, the Pioneer work of Pierre-Paul Grasse in termite colonies revealed the communication mechanisms of these insects by means of chemical signalling and in particular by pheromones [7]. These observations resulted in an ant-based exploration algorithm [8]. Here, each ant leaves a pheromone trail in its foraging activity. This trail persists for some time and it is followed by other ants in the search of food resources.

Also, the pheromone approach has been widely adapted to several artificial intelligence problems in its converse flavour (i.e. anti-pheromones) [9]–[11]. In particular, some researchers have used anti-pheromone (APH) proxies to optimize robot exploration [12]. The main advantage is that each unit accesses a different region fostering the diversity of the solutions by means of indirect and decentralized communication.

On the other hand, the efficient exploration and target localization in urban environments is gaining more and more attention [13], [14]. However, bio-inspired algorithms tailored to optimize robot exploration and dynamic route generation in SC are somewhat separate research fields. Therefore, in this work we propose an APH-based robot swarm exploration strategy to optimize routes in SC. In particular, we merge robotics knowledge with the SC paradigm to analyse intelligent routing of cooperating electric vehicles. We describe how a simple APH-based algorithm can be effective in locating targets in different cities. To this end, we use both numerical simulation and real physical exploration with three prototypes.

This paper is organized as follows. In Section 2 we present the APH-based algorithm and Multi-Agent architecture for SC exploration. We apply the strategy in Section 3 for a case study of 4 different cities with different spatial complexity. The main outcomes from this study are summarised in Section 4 and we conclude in Section 5.

2 An Anti-pheromone swarm algorithm for exploration

In the following we describe both the proposed architecture and the Anti-pheromone based algorithm.

2.1 Proposed architecture

For the distributed execution of the Anti-pheromone swarm algorithm we have used the multi-agent architecture PANGEA [15], previously developed in the BISITE research group. This Multi-Agent System (MAS) allows the implementation of embedded agents in computationally limited devices, allowing a simple communication among the different elements. The information transfer is based on the use of the ISO / IEC 20922: 2016 protocol, which allows flexible communication with optimum battery consumption

Virtual agents in a MAS cooperate with each other, aiming to solve a problem or reach a goal. In PANGEA, agents with the same goal are grouped into virtual organizations (VO). Fig. 1 shows an interaction diagram of the different virtual organizations implemented in our study. Below we describe the virtual organizations in this work.

- **Mobility:** Includes mobile agents for environment exploration.
  - **Robots:** mobile entities that move around the environment and eventually find targets.

- **MQTT:** is the technology used for receiving and resending robot messages by means of the MQTT (MQ Telemetry Transport) protocol [16].

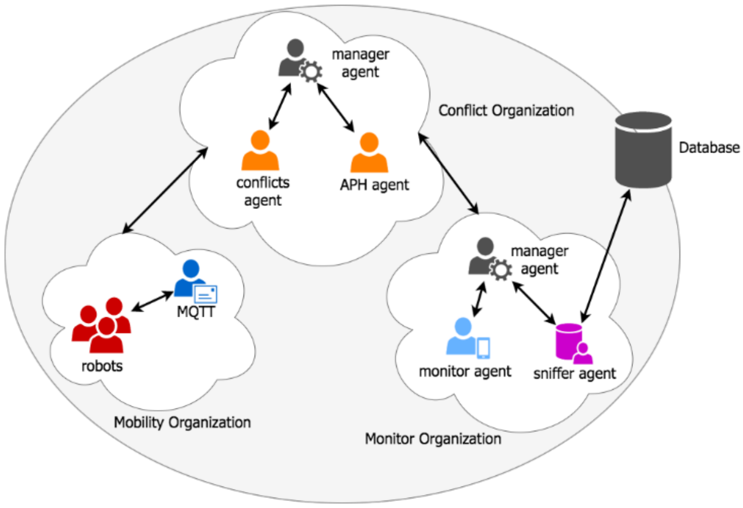

Fig. 1. MAS architecture. Three virtual organizations (Mobility, Conflict and Monitor) of agents cooperate in the navigation process. The robots of the Mobility VO communicate through the MQTT agent. The Conflict VO manager receives the robot information and sends it to the conflicts and APH agents. He also sends back mobility instructions to the robots. All these messages are also monitored in the VO Monitor and finally stored.

- **Conflict:** includes the following agents:
  - **APH agent:** it holds the virtual map and is responsible for counting the anti-pheromones at every location and time.
  - **Conflicts agent:** Aimed at solving potential emerging conflicts among agents when two robots coincide at the same location.
- **Monitor:** to monitor the process and store the information in a database. These agents do not interfere in the main process. This group is composed of:
  - **Monitor agent:** controls the life cycle of other agents and enables the interface to display the general state of the communications, organizations and agents. This agent is responsible for starting the agents of the platform in case of failure.
  - **Sniffer agent:** manages the message history and filters information by controlling communication initiated by queries.

In PANGEA the Manager agent verifies the creation and elimination of agents and the assignment of roles. Also, he is the communication hub among organizations.

2.2 Anti-pheromone algorithm

The navigation algorithm we present in this work (pseudocode in **Fig**. 2) is an adaptation of the classical two-dimensional APH gradient [4] to a 1D gridded world. This world consists of a set of parallel and perpendicular lines arranged in a way that mimics urban topologies.

```
while current location ≠ target do
    if current location = intersection then
        [paths] ← get all paths with the lowest and same level of
          anti-pheromones;
        if  size (paths) > 1 then
            angle ← angle of random path in [paths];
        else
            angle ← angle of the path in [paths];
        end
        turn ( angle );
        go on;
    else if current location = dead end then
        turn ( 180° );
    else
        drop anti-pheromone;
        go on;
    end
end
```

Fig. 2. Anti-pheromone navigation algorithm. Each time a robot reaches an intersection which is neither a target nor a dead end, a negative APH gradient based route is followed.

In the following section we apply this strategy to different scenarios.

3 Simulation

In this section we describe both the numerical simulations and the laboratory robot prototype based tests.

3.1 Numerical simulation

Our simulation consists of an NxN gridded world where robots move along paths generated according to a modification of the random walk algorithm as we explain below. In this setting we define the following parameters:

1) N_{robots}: number of robots
2) $R_{maze} = N_{path}/N \cdot N$ proportion of path units (N_{path}) with respect to the total number of cells.
3) $Pers_{rate}$: pheromone evaporation time (i.e. number of time units a pheromone takes to evaporate). At every time step the robots leave a pheromone unit.

There are two phases in our tests. Firstly, we generate synthetic topologies with parametrized complexity. Here the path generation algorithm is a simple adaptation of a 2D random walk with jumps of varying lengths. We however constrained the algorithm to avoid adjacent lines and prevent robot collisions. With this strategy we generated a population of 22x10^6 samples by sweeping parameters as follows: $N = 40$, $N_{robots} \in [1, 10]$ with $steps = 1$, $R_{maze} \in [0.1, 0.6]$ with $steps = 0.05$ and $Pers_{rate} \in [1, 100]$ with $steps = 1$. For each parameter combination we repeated the tests 50 times. At every run, a synthetic topology is generated and both the target and robots' initial positions are selected randomly among the path locations.

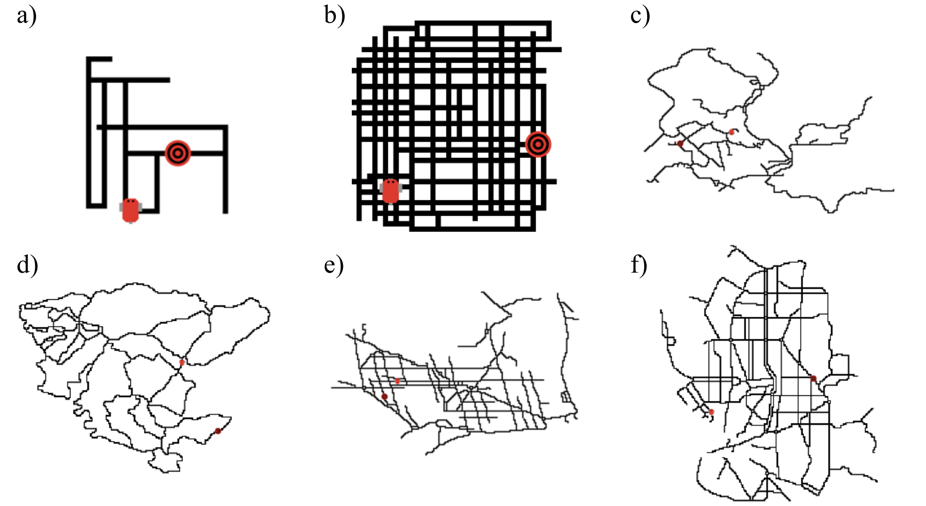

Fig. 3. (a) Synthetic topology with $R_{maze} = 0.1$. (b) Synthetic topology with $R_{maze} = 0.5$. (c) Map of Gijon with NM = 2.01. (d) Map of Castellón with NM = 2.02. (e) Map of Barcelona with NM = 0.6. (f) Map of Madrid with NM = 0.5.

In the next phase we have used real EV maps from four Spanish cities. In particular, the bike routes from Madrid, Barcelona, Gijon and a mountain bike trail in Castellón have been adapted to our simulations.

For each of these maps, we ran a parameter sweep with $N = 200$, $N_{robots} \in [1, 5, 10]$, and $Pers_{rate} \in [10, 250]$ with $steps = 10$.

As before, every combination of parameters has been repeated 50 times and the target and robot initial positions are chosen randomly at every iteration.

In both analyses (synthetic maps and real routes) we have obtained the following metrics:

a) $firstTime$ defined as the first time of arrival to the target by any of the robots,
b) $totalTime$: elapsed time until all the robots reach the target.
c) $robotPath$: the number of discrete locations (i.e. patches) covered by the robot along its path.

As stressed, every topology is parametrized by its spatial complexity. This is simply defined as the mean of the neighbourhood (Von Neumman) size of every path cell. The resulting complexities for Gijón, Castellón, Madrid and Barcelona are respectively: 2.01, 2.02, 2.05 and 2.06 (Fig. 3).

3.2 Robot Swarm Simulation

We have also built real robot prototypes in order to test the APH navigation strategy in the laboratory. The reason for using real robots in our experiments is that, as electric vehicles, they are subjected to events which are similar to those commonly found in real EV scenarios. In particular, the measurement errors of position in a real environment map to our prototype setting. Moreover, the lab tests allow us to explore the robustness of our approach, which is the major concern in real implementations.

To this end, the electronics division of the BISITE research group of the University of Salamanca has built a set of three robots following the schematics shown in Fig. 4.a

An Arduino board is used as microcontroller. The rotors control is enhanced through a driver based on the chip L298n. The sensing system consists of two parts: a) an infrared sensor array for edge line detection and an ultrasound sensor to track distances. The WiFi communication has been enabled through an ESP8266 board. The robot holds a 2 cell Lithium 800mAh based battery.

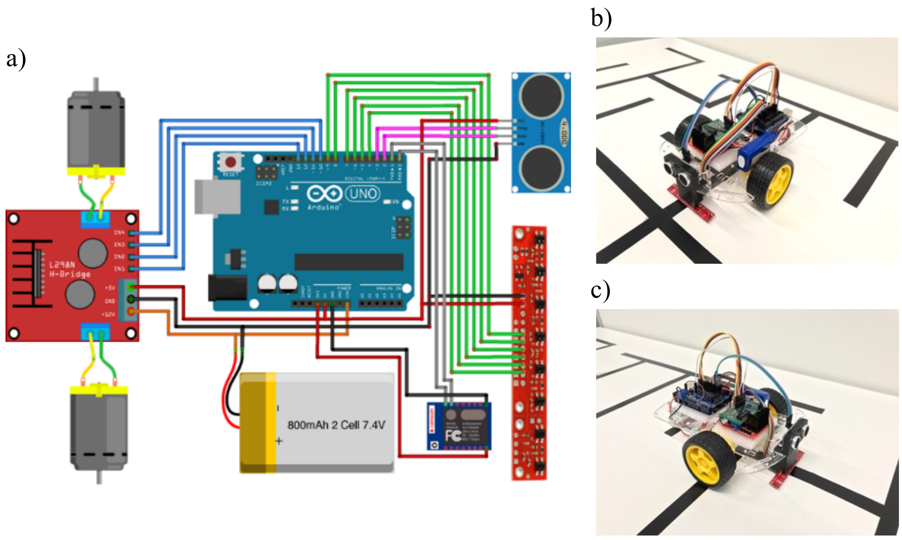

Fig. 4. a) Schematics design of robots. Electronic components and design of the robot connections. b) and c) Robots in lab controlled environment. Here the robots move along black strips by means of an 8 sensor array located at the front side (red component).

The laboratory tests have been implemented with the MAS design proposed earlier in this work. The map has been constructed by printing connected segments of black lines on a white surface according to the general patterns in our simulations.

Each robot moves forward through the lines until it reaches an intersection. Then it sends an MQTT message to the Conflicts and Monitor VOs to determine the next move. This is done by counting the current APH level of the possible paths at the cross and by selecting that with the minimum APH amount. Once the path is selected the APH level is updated. The agent states and decisions are stored in a database for its posterior statistical analysis.

4 Results

In this work we analyse the mean first time of robot arrival to the target averaged over the 50 runs for every parameter combination. We use this observable as a proxy for robot collaboration. In Fig. 5 we show this metric for a value of 60 $Pers_{rate}$ and increasing number of robots and for different levels of map complexity in a log scale. Here the times are normalized with the maximum time and the map complexity is computed as described above. Also in the plot we show data points corresponding to simulations with 5 and 10 units for the bike routes for Madrid, Barcelona, Gijón and Castellón (Fig. 3).

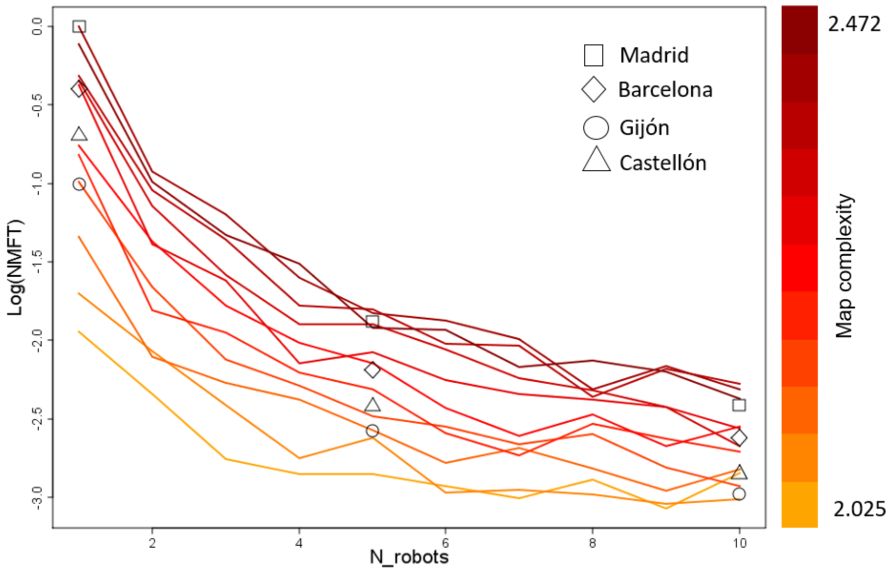

Fig. 5. Normalized first arrival times to the target for different number of robots and levels of map complexity. Data points represent the simulation on real bike routes in four Spanish cities.

It is observed that arrival times decrease with the number of robots. This result shows that swarm collaboration is actually happening. Also, as expected, the complexity of the map topology augments the exploration time for a fixed number of robots. For 10 robots the NMFT for Gijón, Castellón, Barcelona and Madrid are: 0.051, 0.057, 0.073 and 0.089 respectively. The complexities of Gijón (2.01) and Castellón (2.02) are similar, which is also the case for Barcelona (2.06) and Madrid (2.05). This is consistent with the disposition of the data points in Fig. 5. Interestingly, Madrid is slightly less optimizable than Barcelona, although its complexity is smaller.

In our setting, we predict that APH based navigation in Gijón-like cities is likely to be around 57% times shorter than Madrid-like cities only due to the differences in spatial complexity (see Fig. 3) regardless of city size.

These simulations have been validated by real tests at the laboratory with physical prototypes. In particular, the dynamics of three units have been monitored to ensure the time reduction found in simulations. Due to limitations of space a comparison between simulations and real time measurements this part of work is left for the future.

5 Conclusions and future works

In this work the classical anti-pheromone ant foraging algorithm has been adapted to the problem of optimal routing in Smart Cities. We have validated our approach both by numerical simulations and by real laboratory tests. The simulations were performed with random-walk generated maps and with real bicycle routes of four Spanish cities with parametrized spatial complexity. In both cases, swarm collaboration is results in a significant reduction of the arrival times. Also, it is found that these times increase with map complexity.

We have validated the possibilities for a real implementation of our strategy in the laboratory facilities of the BISITE research group at the University of Salamanca. To this end, three prototypes have been constructed to check the proposed MAS architecture and the robustness of the APH based strategy in real conditions.

From the statistical analysis of the experiments the collaboration among robots has been quantified in terms of the elapsed times to reach a target. We have shown how an increase in the number of units and in map complexity results in higher exploration times. The swarm collaboration mechanisms of our design has shown to be effective both in simulations and laboratory and can be implemented in real Smart City scenarios.

Regardless of the topology of the city, the proposed decentralized collaborative navigation strategy can be valuable to the design of new routing patterns without compromising efficiency. At its current stage the navigability improvement is only shown when compared with the non-swarm limit. Due to limitations of space and time the comparison with other mobility solutions is left for future work.

In future works, we will also consider combinations of different bio-inspired algorithms to improve city navigability under different factors. In particular, a suitable combination of different virtual signalling communication mechanisms (e.g. pheromone and anti-pheromone) can lead to significant improvements.

Although in this paper the real laboratory tests have been used only as a proof of concept for our APH MAS design, in a future work a systematic analysis of the prototype dynamics will be performed in order to verify the numerical simulations.

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