Simulated Ant-agent Aspects for Defining an Ant-bots Ontology

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***Abstract*—Swarm intelligence systems, wherein robotic devices encoded with collections of discrete abilities executed at individual levels to cause swarm level emergent behaviour are appealing to fields, such as nanotechnology. Such swarm intelligence systems are typically used to solve complex real-life problems at, often, minimal costs. For example, ant colony systems have been proposed for deriving solutions to tough problems by emulating the behaviours of natural ants. Solutions to complex optimisation problems such as the bridge crossing problem, vehicle routing problems, shortest path formation problem, and travelling salesman problem have been presented. This study takes inspiration from the various simulated ant colony systems, investigating the low-level actions and abilities of simulated ant-like robotic devices towards prescribing an ant-bots swarm intelligence ontology. In this context, an ant-bot is assumed to be a tiny naive autonomous robotic device built on the characteristics of simulated ants. On its own, an ant-bot would not achieve anything practical. However, as a swarm, ant-bots can create compelling emergent behaviour. We investigate the discrete aspects of simulated ant agents that cause emergent behaviour and explicitly cogitate them in the design of an ant-bots swarm intelligence ontology. Experimental tests connoted three such aspects as the building blocks of the desired swarm intelligence ontology. First, the swarm space captures metadata about the configuration of the simulated environments, targets, and any global swarm rules. On the other hand, ant-bot context emphasizes the individual abilities and activities of ant-bots. Last, the swarm interaction aspect apprehends the embraced communication mechanism, whether direct or indirect, local, or global, nature inspired, mathematical, biological, or otherwise. Commendably, the swarm intelligence ontology thereof is a mere formal ant-bot knowledge representation model.**

Keywords: ant-bot; swarm intelligence; ant-bot ontology.

I. Introduction

Swarm intelligence focuses on the design of intelligent multi-agent systems based on the collective natural behaviour of social colonies, such as ants, termites, birds, spiders, and bees [1]. It is a comparatively recent problem-solving method that draws inspiration from nature [2]. However, the methods governing the behaviour of natural colonies remains unknown. Although cooperative colony behaviour emerges from relatively straightforward relationships between the colony members, what exactly does each member do to cause colony level behaviour?

Ants are fascinating. Related ant systems have received much attention because of their practical application to combinatorial optimisation problems [4] such as shortest path formation [5]. However, what does each simulated ant agent do for swarm convergence? How do we formalize the representation of the knowledge insinuated in ant systems towards a more visible practical use in real life problem solving?

An ontology is a philosophical branch that investigates the concepts of existence, being, becoming, and reality [6]. A swarm intelligence ontology, therefore, refers to a collection of the swarm knowledge related to swarm members behaviour, swarm member abilities, the environment in which the swarm is deployed, as well as all the other meta parameters of the swarm. This study seeks to understand the design of an ant systems inspired swarm intelligence ontology.

A. Problem statement

Creating an ant-bots ontology connotes coordination of homogeneous swarms. Pushing this agenda further to the coordination of heterogeneous swarms is an ambitious project which involves understanding various discrete swarm intelligence ontologies. For example, we would require independent ants, termites, bees, social spiders, fish, or birds ontologies before we build a generic swarm intelligence ontology that may tackle heterogeneity.

Simulated ant systems are fascinating. What are the building blocks of an ant-bots ontology that may contribute to the development of heterogeneity in the swarm intelligence body of knowledge?

Little has been said about ant-bots abilities to create emergent behaviour. Individual actions of ant-bots, communication, interaction strategies, decision-making, and the information they generate are blurred ingredients of swarm knowledge. Representation of this knowledge has not, yet, been formalized, which is the theme of this study. The article seeks to pinpoint and characterize the key aspects of simulated ant systems that define an ant-bots ontology. Achieving this involves conceptualization of the environment in which ant-bots operate, the design of the ant-bots, and an understanding of the processes through which ant-bots interact, communicate, share, or create knowledge. In the end, we seek to demonstrate an informed understanding of the prospective vocabulary of ant-bots towards improved application and visibility of ant systems. To the best of our knowledge, formalized representation of ant systems in the form of an ontology is a creative intervention in the field.

 ISBN: 978-1-68558-053-7

B. Overview

The article is structured as follows: Section II presents literature which identifies the predominant ant system aspects that may inspire the design of an ant-bots ontology. Section III goes on to characterize the identified aspects, taking us closer to pinpointing the component units of the envisioned ant-bots ontology. In Section IV, the actual ant-bots ontology is proposed before we conclude the study in Section V, highlighting the contributions we make, as well as pointing the direction for future work.

II. RELATED WORK

Research intervention to represent knowledge substantively and methodologically is visible [8]. Although we note attempts in the literature to create swarm intelligence ontologies inspired by the functionalities of ant colony systems, bee colony optimisation models, particle swarm optimisation systems, and even heuristic particle swarm ant colony optimization models, such specificity and explicitness in the representation of ant-bots knowledge is still blurred. This study seeks to investigate specific aspects of simulated ant systems to then suggest an explicit ant-bots ontology.

Closest in the literature are works that investigated the meaning or purpose of pheromones in directing ant-like agents moving between two points [2]. These works established pheromones as indirect guides towards agents' targets. Pheromone mark the paths ant agents probabilistically follow. Directions are selected stochastically based on the levels of pheromone around a decision-making ant agent. We refer to direction selection by ant-bots as orientation. This understanding of the meaning of pheromone as guides to ant agents has been modified and optimized many times [9]. Although all the hybrids yielded maintain the same concept of pheromone perception for orientation, heuristic information is required to bring about optimal solutions [10][23]. For example, defining swarm memory abstractly as held on the environment is a heuristic feature to merely reducing the cost of managing ant-bots.

Most ant systems insinuate ant agents that also possess some internal state in which to keep the swarm goal [19]. Each ant agent is always aware of its target, implying knowledge of which levels of pheromone are attractive or repulsive at the time [19]. Therefore, flipping between different internal states is a reward that comes with an ant agent finding the target or successfully returning to the nest [19][21]. During the search for the target or nest, it is a standard that ant agents drop and update specific levels of pheromone depending on their internal state [10][22]. Pheromone updates are also heuristically administered through dissipation processes [19] to optimize swarm convergence quality and speed. Summarily, most ant systems achieve mission planning and execution through (a) pheromone management policies (detection of the levels of pheromone around, dropping new levels of pheromone at current location, updating the quantities of pheromone held at current location, and pheromone dissipation), (b) internal state transitions (heuristically managing context awareness, and ant agents flipping between internal states when it becomes necessary), as well as (c) local search procedures (orientation and movements).

A survey of the theoretical meaning of ant colony optimisation [11] has also been presented. Emphasis has been on understanding the theoretical basis of swarm convergence on optimal solutions given that stochastic methods drive the processes. However, trust level computation demonstrated in [12] notably insinuated the value of similar swarm aspects for recommendation towards an ant-bots ontology [13]. The primary goal of this study is to explicitly elucidate the key aspects of ant systems that may inspire the design of ant-bots ontology for more visible application of related swarm intelligence systems in real life.

III. METHODS

This study is still in the infancy towards the creation of heterogeneous ontologies. It focuses on understanding a particular homogeneous ant-bot ontology that will be integrated with other homogeneous ontologies towards addressing heterogeneity in swarm intelligence models. Precisely, we conduct (a) a requirements elicitation exercise (seeking for what matters in the design of an ant-bots ontology), (b) requirements specification (looking at how each elicited aspect fits into the problem) and (c) administer the ontology modelling and proposing a methodology for integrating these aspects.

Design science research is adopted when the main computational artifacts of the study are defined [14]. In proposing the ant-bots ontology, emphasis is invested on achieving scalability, reproducibility, and adaptability. A positivist school of thoughts drives the study towards understanding the veracity of the work [15] through deductive means [16][17] until an ant-bots ontology ensues. Hopefully, the results we yield should be transferable from views to theory [18]. The next sub-sections give detailed analyses of those aspects prevalently insinuated when ant systems are studied.

A. Ant-bot architecture

An ant-bot is designed with basic memory in which to hold four key pieces of information pertaining to its position, internal state, neighbourhood, and the available instruction set as shown in Figure 1. Awareness of the current position allows an ant-bot to retrieve the levels of pheromone held on that position. It allows the ant-bot to be able to update specific levels of pheromone at its location in specific quantities. Positional awareness is an individual ant-bot property.

The internal state keeps the ant-bot's purpose in the swarm. At any point, an ant-bot is either searching for the target or travelling back to the nest. In each mode, an ant-bot places a different type of pheromone on its current position, thus updating the swarm's global information. Often, an ant-bot places pheromones attractive to other ant-bots in the opposite internal state mode. For example, an ant-bot searching for the target places pheromones that are attractive to ant-bots that are travelling back to the nest. Those ant-bots travelling to the nest places pheromones that are attractive to

 ISBN: 978-1-68558-053-7

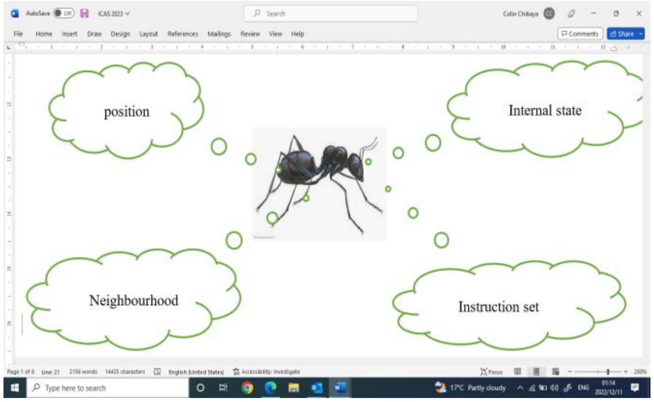

Figure 1. Ant-bot design

ant-bots searching for the target. That way, trodden paths emerge at swarm levels.

Also, every ant-bot is designed with the ability to perceive its neighbourhood. The neighbourhood comprises candidate locations an ant-bot may move to. Each location in the neighbourhood is assigned some weight based on its attractiveness or repulsiveness. Such attractiveness or repulsiveness of nearby locations is based on the amounts of specific levels of pheromone they hold. An ant-bot stochastically decides on where to go based on the attractiveness or repulsiveness of the locations around it.

Last, ant-bots follow deterministic instructions to achieve their goals. They are designed with the ability to follow these instructions at individual level towards achieving swarm level emergent behaviour. A collection of these instructions and their parameters is described further in the next section on ant-bots actions. This work does not dwell on the engineering side of the design of ant-bots.

B. Ant-bots actions

It is apparent that ant-bots drop specific levels of pheromone as they navigate the environment. The action of dropping pheromone updates the quantities of this specific level of pheromone held on the ant-bot's current location. The quantity of pheromone held on the environment creates a shared memory for the swarm. Holding these quantities on the environment has the advantage of freeing ant-bots from the need to have large memory capacity. It also separates the ant-bot's life from the swarm solution. When an ant-bot drops and updates specific levels of pheromone at its current location, that action also updates the swarm level shared memory. Listing 1 presents the concept of dropping pheromone in computational terms.

Listing 1: dropping levels of pheromone

```
Drop (int x, int y, int Qty)
{
  update(level,Qty + read (level, x, y))

}
```

Precisely, an ant-bot reads the quantity of the levels of pheromone, at current location, that are repulsive at the time, and update the same levels by a prescribed quantity.

The next step for an ant-bot would be to relocate, after dropping specific levels of pheromone at the current position. This requires an ant-bot to, first, orientate before following some direction. Orientation, in computation terms, refers to an ant-bot detecting the attractiveness or repulsiveness of neighbouring locations before choosing a direction. This is achieved by weighting neighbouring locations based of the levels of attractive and repulsive pheromone they hold. Locations that have more attractive than repulsive levels are favoured while those locations with more repulsive than attractive levels are penalized. Listing 2 presents the concept of orientation algorithmically.

Listing 2: ant-bot orientation

```
Orientate (int x, int y)
{
  for each nearbyLocation i
  {
  wi←qtyAtt(x±[0,1];y±[0,1])−qtyRep(x±[0,1];y±[0,1])
  }
    set a scaled roulette wheel for wi
      direction ← randPick (i,wi)
}
```

The equation in the loop in listing 2 shows how the weight of each location around an ant-bot is calculated. Once these weights are known, a stochastic roulette wheel is established where more attractive locations are allocated wider spans than repulsive locations. Random selection of a location in such a setup favour selection of attractive rather than repulsive locations. Great in this approach is that even very repulsive locations can still be stochastically picked to bring about randomness in the movement. However, it would be rare that a repulsive location gets picked.

Ant-bot movement follows successful orientation. Movement is about relocation in the orientation direction. The aspect of movement is interpreted in listing 3.

Listing 3: ant-bot movement

```
Move (int x, int y, direction i)
{
   x ← x + direction (ix)
   y ← y + direction (iy)
}
```

In this case, an ant-bot would move from its x coordinate towards the x direction of the direction of orientation. It would move from its y coordinate towards the y direction of the direction of orientation.

Eventually and at some point, a moving ant-bot will hit its target. This achievement triggers the flip state action. An ant-bot that was searching for a food target would change its role in the swarm to start looking for the nest. It would change its perception of which pheromone is attractive and repulsive. Also, it would flip the levels of pheromone it drops on visited locations, assuming opposite phenomena thereafter. Listing 4 describes flipping between different internal states.

Listing 4: ant-bot flip state

```
state Flip (int x, int y)
{
    if (x ; y) has Target
     return homing
    if (x ; y) has Nest
     return searching
}
```

Precisely, this aspect conditionally returns a particular internal state depending on the location of the ant-bot at the time. An ant-bot that finds itself at the target because it was searching for a target should change to homing, where it starts the journey back to the nest. An ant-bot that finds itself at the nest because it has been homing should flip to the searching mode and commence the search trips all over. This function will only have effects on these two targets. Otherwise, a searching ant – bot that has not found the target would continue searching. An ant-bot travelling the nest, that has not reached the nest, will continue homing until it finds the nest. A collection of all ant-bot actions from the ant-bots instruction set was shown in Figure 1 earlier on.

C. *Heuristic aspects*

The ant-bot systems utilize two key heuristic elements. These swarms of ant-bots operate in deterministic environments that include specific locations, pheromone levels, and the context in which the ant-bots exist or navigate as they solve problems. The environment serves as a shared memory for the swarm. Figure 2 shows an example of this environment, depicted as a grid of locations where the ant-bots can move and leave pheromone behind. The parameters of this environment are set during the simulation process.

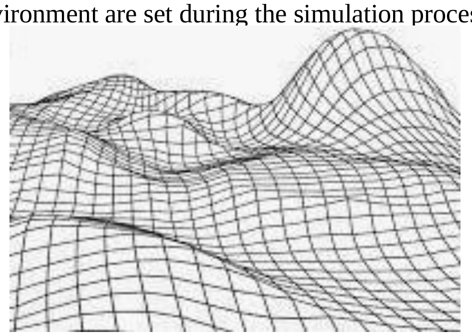

Figure 2. Ant-bots environments

Interesting is that the pheromone levels dropped on different locations of the environment may virtually dissipate through evaporation or diffusion. Pheromone dissipation is an elitist approach for smoothen the pheromone paths formed. It is also a mechanism with which old solutions may be forgotten in favour of new outcomes. Although these aspects are not directly associated with the life of an ant-bot, they contribute to ant-bot behaviours, hence required in the design of an ant-bots ontology.

IV. ANT-BOT ONTOLOGY

Figure 3 visualizes the integration of ant-bots architecture, ant-bots actions, and the related heuristic aspects into an ant-bot ontology. The proposed ontology primarily shows the locations of different pieces of ant-bot knowledge. The centre or core of the ontology holds the

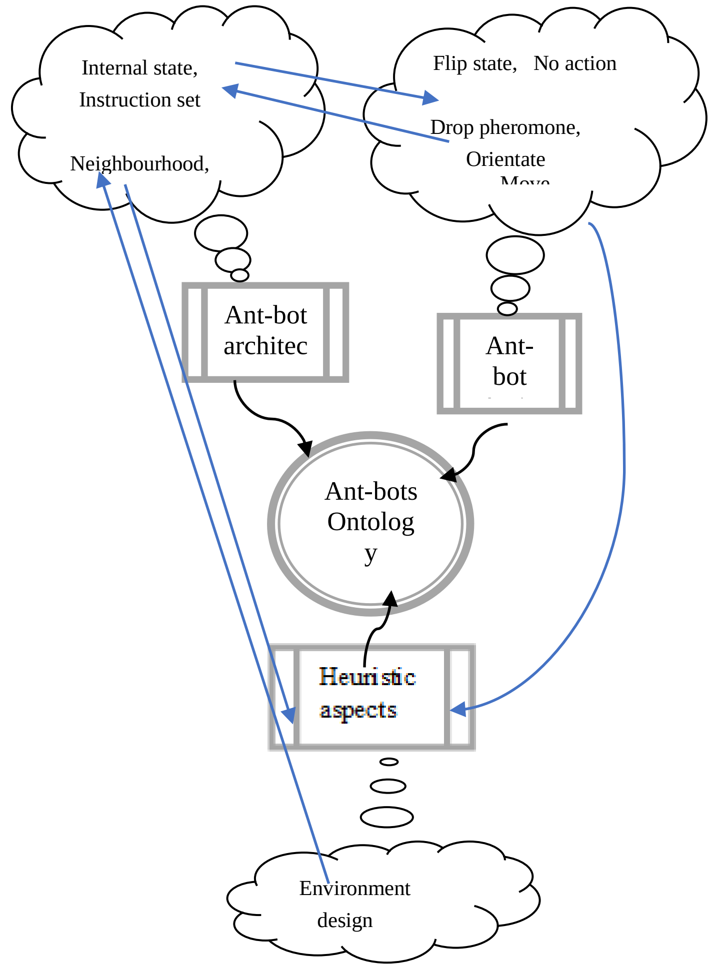

Figure 3. Ant-bots ontology

widespread representation of swarm level knowledge which synchronizes knowledge from the supporting sub-domains. The heuristic aspects have to do with environmental designs and how the pheromone levels deposited on the environment are maintained and smoothened beyond ant-bot abilities. Also, the core is aided by the ant-bot architecture which captures positional knowledge, internal states details about each ant-bot recalling its goal in the swarm, its neighbourhood, and how each ant-bot uses the instructions held in the ant-bots actions knowledge domain. The

 ISBN: 978-1-68558-053-7

instructions include actions such as drop pheromone, move, orientate, and flip state.

It is pertinent to note that the survival of an ant-bots swarm depends on the strength of the shared memory defined by the levels of pheromone held on the environment. Low levels of pheromone on the environment connote lack of swarm level knowledge of the location of the target, hence random movements. On the other hand, excess levels of pheromone would saturate the environment and deplete the formed paths. A balance is struck through elitist heuristic means, including pheromone dissipation.

In this study, we do not concentrate on detailing implementational concerns. Instead, we are concerned with the logic for emulating ant behaviour. We want to focus on figuring out what each ant-bot does at an individual level to achieve swarm level emergent behaviour. We are concerned with the understanding of homogeneous swarms of ant-bots where each is simple and autonomous. In this case, the ontology connotes only stigmergic communication indirectly mediated via the environment [19][20]. None of the ant-bots can pass direct messages to others. However, it is possible that an ant-bot may choose not to do anything when it becomes necessary, hence inclusion of a No action aspect in the ant-bot instruction set.

V. Conclusion

This article investigated those aspects of ant systems that cause emergent behaviour and interpreted each in computational perspectives. It went on to suggest a way of putting those aspects together into a knowledge representation framework which we referred to as an ant-bots ontology. The ant-bots ontology is envisioned to capture all the key aspects for coordinating swarms of homogeneous ant-like robotic devices. Unfolding the elements of the ant-bots ontology is essential to providing a detailed modelling scenario that can be applied to other swarm formations. Precisely, the clarity sought in the design of the ant-bots ontology can propel application-specific modelling of solutions to practical problems. The ant-bots ontology presented in this article comprises three knowledge domains which are interrelated to the core domain. These three aspects, together with their relational inferences form the ant-bots ontology.

A. Contributions

Three contributions emanate from this study as follows:

- The article suggested a formal knowledge representation approach for defining ant inspired swarm intelligence systems. This literature extends content in the field.
- Proposals aimed at formalizing knowledge representation in swarm intelligence models are upcoming. This work is one of many studies aimed at understanding the key knowledge domains of swarm intelligence systems, focusing on ant systems. Although this is a discrete case, it guides us towards generic views.
- Although the focus was on understanding an ontology for a homogeneous swarm of ant-bots, the work creates a baseline upon which heterogeneity may be tackled.

B. Future work

Four ambitious directions for future work are envisioned from this study as follows:

- Corroboration of ant-bot knowledge representation through practical experimentation is upcoming.
- An ant-bot ontology could be enriched through incorporation of applicable aspects to cover a wider scope of use cases. It must be tested for completeness, optimality, applicability, and expandability.
- Integration of the ant-bots ontology with other swarm intelligence ontologies may, eventually, bring about practical heterogeneous swarms.
- It is worth pursuing the extensibility of the ant-bots ontology to deal with fuzzy situations, uncertainty, incompleteness, inaccuracies, vagueness, or impreciseness.

Acknowledgment

We acknowledge both the moral and technical support given by the Sol Plaatje University, department of Computer Science, Data Science, and Information Technology. This research was funded by the ABSA research grant, as well as the CAIR project (Centre for Artificial Intelligence Research) grant, with the grant agreement number: CSIR/BEI/HNP/CAIR/2020/10, supported by the Government of the Republic of South Africa, through its Department of Science and Innovation (DSI).

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