2022 International Conference on Intelligent and Innovative Computing Applications
https://doi.org/10.59200/ICONIC.2022.024

An Ontology Based Knowledge Representation for Coordinated SS-bots

C. Chibaya, S. Verkijika, K. Madzima, L. Makhoere, F. Matsebula, A. Mwanza and A. Whata
Sol Plaatje University, Kimberley, South Africa
colin.chibaya@spu.ac.za, silas.verkijika@spu.ac.za, kudakwashe.madzima@spu.ac.za,
lucky.makhoere@spu.ac.za, Fezile.matsebula@spu.ac.za, alfred.mwanza@spu.ac.za,
albert.whata@spu.ac.za

Abstract
Collective behaviour empowers biological species to achieve remarkable swarm level results through distributed actions. For example, social spiders achieve coordinated activities that can lead to plausible outcomes such as preying, mating, or building webs. Developers of simulated swarm systems are increasingly moving away from insinuating individualistic robotic devices, gravitating towards collective swarms to achieve common goals. However, for this to happen, it is imperative to understand the principles that underpin successful simulated coordination of robotic devices in swarms. In this article, we investigate the principles behind artificial swarm systems built on the instinctive behaviours of simulated social spider-like devices (SS-bots). We classify these principles into six interconnected knowledge domains, including (a) environment, (b) SS-bot architecture, (c) SS-bot mission planning, (d) SS-bot communication, (e) SS-bot operators, and (f) metadata and swarm-level data. The key features of each domain are discussed, and an SS-bot ontology is proposed.

Keywords: SS-bot, SS-bot ontology, social spider

1. Introduction

Swarm intelligence is about large multi-agent systems demonstrating emergent behaviour beyond the scope and abilities of the individual swarm members. In this context, emergent behaviour is about the creation of swarm-level outcomes from the individual actions of the members of the swarm (Chibaya, 2014). This phenomenon is, commonly, observed in natural social groups such as herds, ant colonies, flocks, bee swarms, fish schools, or social spider swarms. Although it is desirable to harness the principles that govern swarm intelligence in different scenarios and interpret the individual-level actions of the swarm members into practical computational routines, we will firstly require scrupulous apprehension of the representation of such low-level actions and how they cause emergent behaviour. An understanding of the computational semantics and clear interpretation of the low-level actions of swarm members will valuably inform proper knowledge representation before we can solemnize swarm intelligence as a practical problem-solving approach. The quest to understand the basis of swarm intelligence in different contexts, pursuit to pinpoint the key vocabulary used by swarm members, as well as the desire to formalize knowledge representation in the context of swarm intelligence, are the key motivating factors for undertaking this study. Although this article focuses on a case study scenario of the understanding of social spider-like robotic devices (SS-bots) in swarms, we hope to contribute a methodology that can be mapped to the understanding of other forms of swarm intelligence systems.

Studies aimed at understanding the principles behind swarm intelligence, pinpointing the factors that cause emergent behaviour, and identifying the key factors in the formation of emergent behaviour are gradually gaining popularity (James et al., 2015; Cheraghu et al., 2021). Intriguing is the interest by researchers to investigate even the extension of such knowledge to the coordination of swarms of heterogeneous members (Saffre et al., 1999). Swarms of heterogeneous members can deal with complex mission too challenging for human to perform (Saffre et al., 1999; Tan and Zheng, 2013), tasks that may present a mammoth assignment to a swarm of homogeneous members (Abosaif and Elrofai, 2020). For example, what form of swarm intelligence can achieve a search and rescue mission in a collapsed mine? What

ISBN: 978-99949-0-888-2

form of swarm can be deployed to retrieve bodies in piles of rubble after an earthquake to search through the wreckage? Search mission in these circumstances may require heterogeneous swarms whose members are built from different perspectives. For example, such swarms may comprise ant-like members for robust and fault-tolerant search (Melaine et al., 2020), as well as bee-like members for a waggle-dance inspired recruitment (Cheraghu et al., 2021; Carrillo-Zapata et al., 2020) of other members when it becomes necessary. Swarms of heterogeneous members are better when homogeneous swarms or human may fail to endure (Abosaif and Elrofai, 2020) because such members' working efficiency may be much better (Carrillo-Zapata et al., 2020).

We understand heterogeneity to emanate from putting together several homogeneous swarms (Melaine et al., 2020). One way to achieve heterogeneity is by gradually building and integrating homogeneous perspectives. If we can create and formalize the representation of distinct categories of homogeneous swarms, emphasizing the key principles in each case, concepts, data, and meta-entities of the homogenous swarms, then heterogeneity can emanate. We refer to such formalized representation of swarm intelligence knowledge as a swarm intelligence ontology. Precisely, swarm intelligence ontologies capture the vocabulary, semantics, and the relationship between the actions of the individual swarm members which trigger emergent behaviour (Li et al., 2017; Bock, 2013). A swarm intelligence ontology, therefore, can vitally define the key components of a swarm system, including the knowledge shared, process through which swarm knowledge is generated, managed, used, and stored. It can define the diverse formats of the knowledge produced and how swarm members interpret the meanings of such knowledge. Additionally, a swarm intelligence ontology may enable logical use of knowledge to allow inferences, discoveries, and decision-making. It would potentially define the security aspects at individual member level, bringing about context awareness. A swarm intelligence ontology should, thus, reinforce internal state management, as well as tracking the influences of the actions of the individual members of the swarm on the emergent behaviour thereto. The overall goal of a swarm intelligence ontology is to therefore, eventually, and gradually, evolve into a swarm language (James et al., 2015; Saffre et al., 1999). Hopefully, new swarm intelligence applications may ensue from the birth of swarm intelligence ontologies. Similarly, successful development of homogeneous swarm intelligence ontologies will, potentially, propel the growth of heterogeneity towards better interoperability and reusability in swarm systems.

1.1. Problem statement

Arriving at a swarm intelligence ontology for coordinating heterogeneous swarm members is an ambitious task. It involves understanding discrete swarm intelligence ontologies for coordinating homogeneous swarm members. For example, an arbitrary swarm of heterogeneous members could comprise ants, termites, bees, social spiders, fish, or birds. In that case we would need to understand an ontology for each type of swarm member before we merge the several homogeneous ontologies into a generic ontology that supports heterogeneity. This article is written with the hope of arriving at such an ontology in mind.

The behaviour of social spiders in nature is fascinating. As a starting point, we tackle the problem of creating a homogeneous swarm intelligence ontology for coordinating spider-like robotic devices, here referred to as SS-bots. The hope is that heterogeneity will ensue when, in future, new ontologies are added to this proposed body of knowledge.

1.2. Overview

We envision the collective behaviour of SS-bots as based on individual decision making and local interactions policies (James et al., 2015; Li et al., 2017; Bouriot and Chevrier, 2020). Collective behaviour is only visible at swarm level (Saffre et al., 1999; Abosaif and Elrofai, 2020) though it is generated at individual SS-bot level. Little has been documented on the nature of the low-level actions and the information SS-bots share. The mechanisms in which SS-bots share information, and the dynamics involved in their decision-making to cause emergent behaviour are blurred. In this case, coordination refers to cooperative actions and movements of SS-bots towards a goal (Melaine et al., 2020). Precisely, coordination in the context of SS-bots is about resolving a search problem (Bouriot and Chevrier, 2020).

Little is known about SS-bots' ability to emulate vibrations and emulate them through simulated

ISBN: 978-99949-0-888-2

communal webs (James et al., 2015). While the actions of SS-bots, such as decision-making, communication, interaction, and generation of vibrations are the key ingredients of the emergent behaviour thereto, how do we holistically represent SS-bots' knowledge in computational terms? How do we formalize such knowledge representation for reproducibility and further use?

This study seeks to pinpoint the component units of a swarm intelligence ontology for coordinating SS-bots. The proposed swarm intelligence ontology involves conceptualization of mission planning, SS-bots internal states, communication, and metadata issues. It involves the representation of SS-bot reasoning and their architectural design. Also, it entails abstracted representation of the environment in which SS-bots operate, depicting the environment as the shared memory for the swarm. Additionally, the ontology captures the representation of any uncertainty, incompleteness, and inconsistencies in the swarm information and knowledge. Consequently, global level policies such as global awareness, and any decision-making made at swarm level are also recorded in the ontology, defining SS-bot context reasoning. The aim of this work is to present an informed understanding of the prospective vocabulary of SS-bots to enhance practical use, application, and visibility of this knowledge domain in problem-solving. Hopefully, representation of the proposed SS-bots ontology creates new content in the field.

Section 2 presents related work in which attempts to understand the design of swarm intelligence are discussed. We focus on discussion emphasizing swarm member interactions, communication, and decision making. Section 3 identifies the key underlaying principles of SS-bot coordination. In Section 4, we further describe the identified knowledge domains of the SS-bots. In section 5, we highlight the contributions we make, as well as pointing towards the direction for future work.

2. Related Works

SS-bots inspired swarm systems function under uncertainty (Abosaif and Elrofai, 2020). They equally rely on the environment, SS-bots, data for decision-making, action planning, and interaction among the SS-bots. The key information needed by the SS-bots is created within the swarm by other SS-bots (St-Onge et al., 2020) or by prey. There have been ongoing efforts to formalize the design principles underlaying such swarms to then solemnize knowledge representation officially in this domain (Zhaoyu et al., 2020). However, we first require a concise understanding of the features of the environments, data and its storage, as well as an apprehension of the mechanisms in which shared memory emerges.

Representation of swarm knowledge using an ontology has been recommended (Li et al., 2017). In doing so, focus is commonly on pinpointing swarm characteristics, dominant design features, popular contexts, SS-bots interaction strategies, mission planning policies, and prevalent decision-making approaches. Notably, literature focuses on understanding swarm processes under uncertainty while noting common constraints and any gaps.

2.1. Related Ontologies

An ontology captures the creation, representation, storage, relationships, and access to knowledge (Bock, 2013). The task to create an ontology is a requirements elicitation exercise where we also stipulate the functional categories, properties, rules, policies, and the relationships between all the aspects of the ontology (Li et al., 2017; Bock, 2013). In swarm intelligence terms, an ontology emphasizes swarm capabilities, SS-bots abilities, and those environment features that influence the SS-bots' behaviours (Tan and Zheng, 2013).

Bids to create swarm intelligence ontologies are ongoing. For example, a multi-agent ontology-based system was combined with a business rule management system (Sadik and Urlker, 2014) and produced plausible distributed control solution to the cooperative manufacturing problem (Navarro and Matia, 2013). To do so, it treated the ontology as a conceptual tool to represent mutual understanding between manufacturing work entities (Carrillo-Zapata et al., 2020). Another ontology was created and merged with a support vector machine for data clustering (Li et al., 2017). In both cases, accurate feedback was noted.

Standardization of knowledge representation in robotics was also achieved using a core ontology for robotics and automation (CORA) (Navarro and Matía, 2013). Here, robotic devices required explicit knowledge representation (James et al., 2015). However, environment aspects were excluded from the key elements of the ontology (Bock, 2013). However, all other abstract representation of the SS-bots actions, interactions, events, and hardware were clear (Bock, 2013). Also, inferential procedures for operating on the

ISBN: 978-99949-0-888-2

data were commonly considered (Li et al., 2017). In addition, and in most cases, emphasis has been placed on improving SS-bots autonomy rather than enabling cooperation and coordination (Navarro and Matia, 2013). The focus has been, often, to enable simpler SS-bots interactions (Srikanth and Sridhar, 2020), enabling knowledge transfer between SS-bots and the environment, representing the key operations, mission planning policies, and detailing the architecture of SS-bots (St-Onge et al., 2020).

Other ontologies are mere references to collective behaviour (Melaine et al., 2020), providing models of systems and the environments thereof, supporting interactions between the system objects and the environment, and stipulating the behaviour of system objects which change the environment (Srikanth and Sridhar, 2020). A few other ontologies provided semantic formalization (Bock, 2013). However, application-specific ontologies are predominantly conceived as too specific and limited to cover generalized requirements. Such ontologies are regarded as too complex (Bock, 2013), which impedes use in generalized contexts (Li et al., 2017). Most ontologies in this category assume deterministic worlds that lack any possibility of uncertainty, incompleteness, or inconsistences in the data (Carrillo-Zapata et al.,2020; Bock, 2013).

Although discrete swarm intelligence ontologies exist, the inferred natural inspiration and the methods followed in their creation differ. Even though we cannot pinpoint a standard way of creating these ontologies, six principles are common. (1) Ontologies need clarity. This means that the terms of the ontology should be clear, independent, and objective. (2) Also, ontologies should be coherent. In this case, inferences should be consistent with the terms of the ontology. (3) Additionally, ontologies should be extensible. This refers to possibilities of scaling the ontology horizontally and vertically. (4) More so, an ontology should embrace modularity. This refers to an ontology being divisible into modules with relevant purposes. (5) Ideally, an ontology may bring about minimal bias. In this case, the description of terms should not rely on a specific encoding approach. (6) In all cases, minimal ontological commitment should be evident. This means that the ontology should support knowledge sharing with minimal constraints to allow flexibility.

We acknowledge the likelihood of diversity between the swarm intelligence ontologies discretely built from different inspiring social colonies. We thus seek to understand the various stand-alone homogeneous swarm intelligence ontologies as building blocks of the generalized versions. As a starting point, we investigate the aspects of a swarm intelligence ontology with which to coordinate swarms of SS-bots.

2.2. Modelling uncertainty

An aspect of swarm intelligence systems that is often ignored in most discussions is consideration of uncertainty (Li et al., 2017) and information incompleteness when SS-bots make decisions. However, ontologies that consider information ambiguity, randomness, vagueness, inconsistency and fuzzy are noticed in the literature (Evangeline and Abirami, 2019). Often, mathematics theories are used to handle such uncertainty through fuzzy logic, Bayesian networks, or Markov networks. Vagueness is better handled using fuzzy logic (Li et al., 2017; Cuevas et al., 2013). On the contrary, randomness, inaccuracy, and incompleteness are best tackled using probabilistic views (Li et al., 2017). However, mathematical approaches focus on annotation (Li et al., 2017), and not resolution of the problems in uncertain contexts. As such, approaches to annotate and support reasoning under uncertainty are still upcoming. IN proposing the SS-bot ontology, we keep the need for reasoning under uncertainty in mind.

2.3. Modelling swarm context

In this case, the term context is synonymous with the environment. A swarm intelligence ontology should include the environment, SS-bots, actions, and interactions between SS-bots (Cheraghu et al., 2021; Bouriot and Chevrier, 2020). Although contexts are often domain-dependent (Melaine et al., 2020), they are all modelled as grids with rows and columns that intersect to form positions (Saffre et al., 1999). For SS-bots, the web is a key component of the context (James et al., 2015). In nature, a web is a non-geometrical network of silk lines that form a horizontal hammock (Saffre et al., 1999). A web represents the plan (Tan and Zheng, 2013) followed by the swarm. The positions on the web represents feasible solutions to the optimization problem (James et al., 2015). SS-bots can move freely on the web. Each SS-bot holds a position, and the quality of the solution pursued is based on the objective function

ISBN: 978-99949-0-888-2

represented by the potential to find the goal (Melaine et al., 2020). SS-bots cannot leave the web because positions outside the web are infeasible. Consequently, the web forms the shared memory for the swarm.

2.4. Modelling the SS-bot

The design and capabilities of the SS-bot are essential. Most designs of robotic devices imitate social colonies (Abosaif and Elrofai, 2020). For example, ant colony systems mimicked the foraging behaviour of ants (Li et al., 2017). Work on SS-bots, in the past, imitated social spider walking pattern (James et al., 2015). In most cases, simulations aim explain the behaviour exhibited at individual levels that causes swarm-level behaviour (James et al., 2015). Concern is mainly on the "how?" aspect and not the "why?". However, what are the required behavioral elements of SS-bots sufficient to explain the swarm intelligence that emanates. What are the low-level activities of SS-bots which causes emergent behavior? How does an SS-bot communicate, decide, generate information, represent, and store related knowledge? How can we mimic SS-bots in computational terms?

An understanding of SS-bots knowledge, and apprehension of the relationship between SS-bots and their contexts can allow the formalization of an SS-bots ontology. The notion that SS-bots complete tasks with limited perception inspire us (James et al., 2015). Knowledge that SS-bots make probabilistic choices with little knowledge of the context is compelling (Saffre et al., 1999). We notice that most decisions are based on the information held in the environment, bringing about stigmergic swarm coordination (Tan and Zheng, 2013; Cheraghu et al., 2021). There is no global organization. All SS-bots are homogeneous simple and autonomous (Melaine et al., 2020). These SS-bots features are elaborated below.

2.4.1 Structural design

SS-bots are classified by gender (James et al., 2015; Carrillo-Zapata et al., 2020; Navarro and Matía, 2013). Male and female SS-bots co-exist (Navarro and Matia, 2013). Female counterparts often outnumber the male by about 70%. Male SS-bots are separated into dominant and non-dominant (Cuevas et al., 2019). Dominant male SS-bots have better fitness and can reproduce by mating with the female neighbours (Melaine et al., 2020). Non-dominant male SS-bots remain close to other male, relying on the dominant males for nutrition (Srikanth and Sridhar, 2020; James et al., 2015; Cuevas et al., 2013). Female SS-bots can attract or repel the male counterparts (Abosaif and Elrofai, 2020). Eventually, emergent behaviour arises, such as weaving (Bouriot and Chevrier, 2020), preying (Abosaif and Elrofai, 2020), homing, or mere searching (Bouriot and Chevrier, 2020). Emergent behaviour results from the activities of the individual SS-bots that contribute to the creation of the shared memory on the environment (Abosaif and Elrofai, 2020).

Each SS-bot has a weight assigned to it based on its fitness (Cuevas et al., 2019). Weights are compared to determine the best fir SS-bot around (Kamath et al., 2018). The worst counterparts are noted (Kamath et al., 2018). Also, every SS-bot has a position and can generate vibrations. Positions are candidate solutions. Therefore, a female SS-bot’s next step is influenced by the nearest best, context, and the global bests SS-bot in the swarm.

2.4.2 SS-bots communication

A specific population of SS-bots is initialized in the environment (James et al., 2015; Tan and Zheng, 2013). Socialization between SS-bots is an ingredient for cooperation and convergence. Vibrations are SS-bots’ mode of communication (Carrillo-Zapata et al., 2020; Cuevas et al., 2013). Each SS-bot seeks to get information about the positions of other SS-bots based on the vibrations it receives. The web is the communication channel (Cuevas et al., 2013; Talamala et al., 2020). Movement around the web is triggered and orientated by vibrations. Information about the location of preys or mating possibilities are communicated through the web (Perez et al., 2016). The intensity of the vibrations is important. It depends on the distance of the source (Navarro and Matía, 201; Zhao et al., 2021), the curiosity of the vibration source, and vibration attenuation over the distance. Thus, every individual SS-bot actively performs local and global searches using vibration sensation (Zhao et al., 2019).

SS-bots do not have a full view of the environment (Carrillo-Zapata et al., 2020; Wignall and Herberstein, 2013). They cannot perceive the complete historic events (Melaine et al., 2020). Thus, SS-bots have limited perception of the environment (Otor et al., 2019; Talamala et al.,

ISBN: 978-99949-0-888-2

2020), emphasizing locality. This defines three types of vibrations (Cuevas et al., 2019), namely, vibration generated when SS-bots move, vibration by the fittest SS-bot, and vibration from the prey. SS-bots can distinguish between these different vibrations and act accordingly. The actions thereto are guided by the received information, including uncertainties and constraints (St-Onge et al., 2020; Navarro and Matía, 2013).

2.4.3. SS-bot mission planning / decision making

SS-bots decisions shape their behaviour. SS-bots commonly trigger such decisions based on their internal states (Cheraghu et al., 2021; Cuevas et al., 2013). One prevalent decision is to move (James et al., 2015 ; Cheraghu et al., 2021; Saffre et al., 1999; Cuevas et al., 2013). Although movement may be random, the choice of where to go is based on the predetermined goal, vibrations, and the shared memory (James et al., 2015). In addition, the gender of the SS-bot also shapes the walk (Cuevas et al., 2013; Zhao et al., 2021). Gender upholds that the female SS-bots move towards stronger vibrations while male SS-bots move towards the nearest female. Female SS-bots are also attracted to gender-neutral SS-bots (Cuevas et al., 2019). Giant female SS-bots are favoured because they create potent vibrations. However, although other factors such as curiosity and reproduction influence like/dislike decisions (Evangeline and Abirami, 2019; Otor et al., 2019)], the final decision SS-bot choice remains stochastic (Cuevas et al., 2013; Zhao et al., 2019).

2.4.4. High level operations

A swarms should maintain a strong community to improve exploration. This is achieved by getting rid of weaker SS-bots on poor fitness grounds (James et al., 2015; Cuevas et al., 2013). The work of Zhao et al. (2019) proposed replacing wort members after each iteration. On the other hand, Cuevas et al. (2019) proposed replacement of the worst fit, replacing these with the offspring from mating best fit members of the swarm. This is an essential swarm level operation that binds the swarm together.

2.4.5. SS-bots constraints

The primary constraint in most swarm intelligence models is lack of inclusion of the time model in the environment. SS-bots movements are, thus, strictly modelled as one single time step per iteration regardless of the fitness value carried, position, or the neighbourhood thereof. It would be ideal to improve aspects of understandability and conciseness in the behaviour of SS-bots. In this vase, understandability suggests that a swarm intelligence ontology would be understood by all stakeholders, other ontology developers, swarm intelligence experts, and even swarm intelligence systems operators. Conciseness, on the other hand, means that a swarm intelligence ontology would consist of a minimal vocabulary to describe the swarm of homogeneous SS-bots. The desire to capture all these aspects in the context of swarms of spider-like robotic devices is the gap this study seeks to fill in the body of knowledge.

3. Methods

An SS-bot ontology can be characterized by six aspects. The core and central aspect is the swarm knowledge. In swarm knowledge, we define the global context of the swarm. This is where data about the other five aspects is synchronized. The environment is another key component of the SS-bot ontology which defines the context in which SS-bots operate. This aspect captures data about the web, its boundaries, structure, the shared memory and any stigmergic factors for SS-bots during their stay on the environment.

Mission planning and related parameters is another rich aspect of the SS-bot ontology. It entails the tools for SS-bot reasoning, design of internal state, meanings of vibrations, parameters that characterize neighbour SS-bots, as well as the triggers to stochastic SS-bot movement decisions. Precisely, mission planning summarizes how path planning and movements are driven (Cheraghu et al., 2021; Cuevas et al., 2013). In SS-bots mission planning, explicit definition of gender plays a key role (Cuevas et al., 2019) towards most decision-making processes (Zhao et al., 2021).

Another key aspect of the ontology is the SS-bot architecture. This aspect considers four SS-bot features, namely, gender, memory, sensory skills, and weights. In addition, SS-bots communication is equally important. This aspect captures the media of communication and the attributes of the medium. In this case, vibrations are characterized with respect to how frequency and the amplitude of a vibration are related to some position on the web, as well as how a vibration is associated with the gender of the SS-bot at its source. Also, the relationship between a vibration, weight, source, amplitude, distance, attenuation, and the gender of

ISBN: 978-99949-0-888-2

the SS-bot is established. The web is the medium through which vibrations are transmitted.

The last aspect of an SS-bot ontology captures the operator and meta-knowledge of SS-bots. In this case, memory about the prey, as well as recalling the frequency of prey vibrations are key triggers of curiosity, mating, or following others. The proximity of prey overrides all other operations in favour of attacking the prey. Thus, most decisions made by SS-bots are based on the different vibrations it receives.

4. Integration of SS-bot ontology aspects

Figure 1 presents the six aspects of an SS-bot ontology. Swarm knowledge is central. This is where the goal of the swarm is defined (mating or preying). Also, this is where initialization of swarm population and other parameters is done, such as setting up gender roles, marking targets, and setting the conditions for achieving the goal.

Figure 2 expands the environment aspect to depict its four parts: the web, its boundaries, and the occupants (SS-bots and prey). SS-bots cannot go to infeasible positions outside the web. SS-bots understand the structure of the web. On the other hand, the web creates a shared memory for the swarm. Both the prey and SS-bots have precise positions on the web. Prey generate unique vibrations attractive to SS-bots. Contrary, SS-bots generate vibrations of different intensity based on gender, weight, and position in the web.

Figure 3 summarizes SS-bot mission planning, depicting four entities. First, an SS-bot's internal state is central in this aspect. It holds the goal of the SS-bot, target, and the resources for achieving the goal. Internal states are influenced by the behaviour of other SS-bots in the neighbourhood, their gender, and other random stochastic actions of the neighbours. Neighbour SS-bots occupy precise positions on the web. They broadcast gender-based vibrations in different intensities. On one hand, male counterparts follow behind the female foils to mate. Only dominant male SS-bots can mate. Non-dominant male SS-bots are meant to balance the population ratio of the swarm.

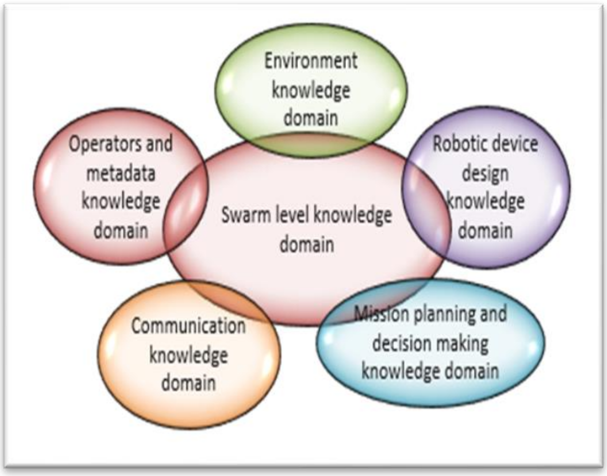

Figure 1. Level 0 ss-bots ontology

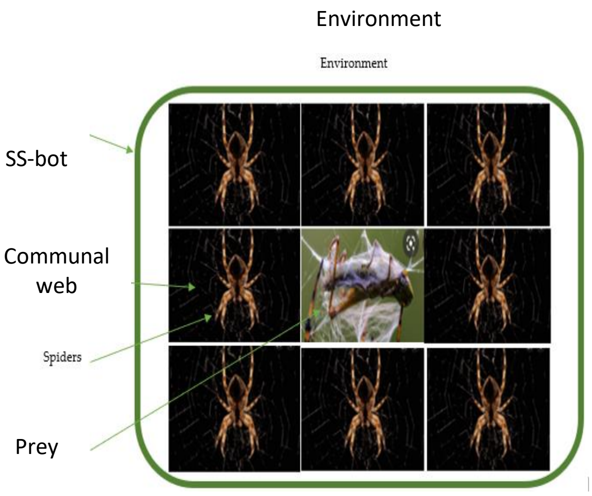

Figure 2. The environment

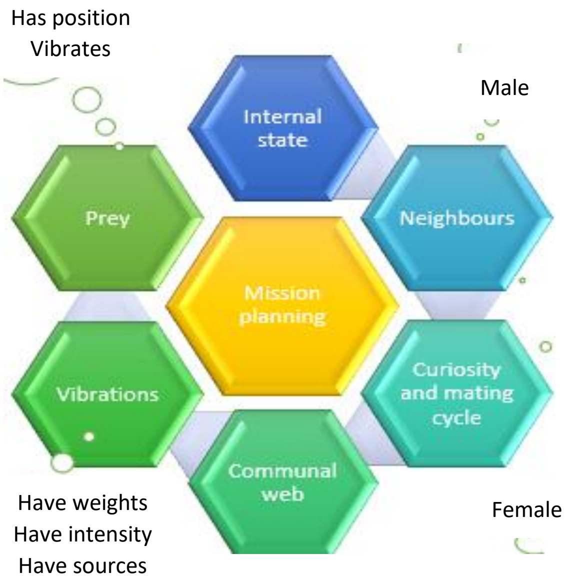

Figure 3. Mission planning in nanites

ISBN: 978-99949-0-888-2

The female SS-bots exert curiosity and anxiety to mission planning SS-bots. Vibrations originate from prey or other SS-bots in the swarm. The decision by an SS-bot to move is, therefore, triggered by other SS-bots around, the vibrations they generate, prey, and all other mission planning factors such as vibration weight, intensity, source, and the gender of the source SS-bot.

Two entities stand out under the communication aspect. These are the web and vibrations (see Figure 4). While the web is a communication medium, vibrations are the signals transmitted via the web. Vibrations are generated at various sources with specific frequencies, intensities, and attenuations. Sources of vibrations are the SS-bots or prey. These sources have specific positions on the web. The intensity of the vibration depends on the distance of the source, gender, curiosity, and the weight. Prey generated vibrations are stronger than those generated by SS-bot. Vibrations from nearby sources are relatively stronger than those from a distance.

The architecture of an SS-bot connotes four parts (see Figure 5). SS-bots have memory, sensory abilities to detect vibrations, gender to stipulate the role, and weight.

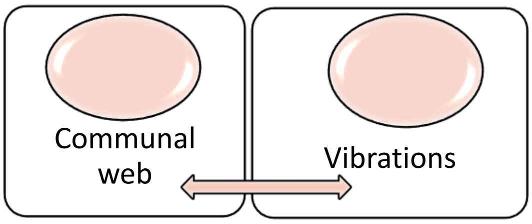

Figure 4. Communication knowledge

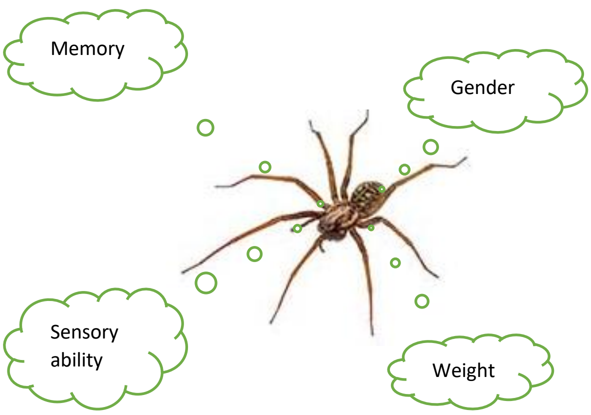

Figure 5: SS-bot design

A collection of operators and metadata define the last aspect of an SS-bot ontology. This is where we keep knowledge about best fit members, worst fit members, and their positions. Although the key decisions are based on the vibrations and other implicit metadata such as the ability of SS-bots to distinguish between vibrations from prey, male, and female SS-bots, these attributes aid decision making in SS-bots and in the entire swarm. Thus, the survival of a swarm depends on the strength of the community of fitter members. Eventually, weak members would be replaced by the offspring of fitter members, updating the shared memory of the swarm with data about fitter members.

Between the distinct aspects of the ontology there is transfer of vital swarm knowledge. For example, vibrations are shared through the web to be used by SS-bots to generate knowledge that influence decision making and internal state. The ability of SS-bots to distinguish vibrations from the prey from those from other SS-bots change SS-bots' features in every movement step (such as weight, position, curiosity, anxiety).

5. Conclusion

We have formalized the representation of SS-bots knowledge in the form of an ontology. Unfolding the elements of such an ontology together with the entities and relations associated with such swarms is essential for providing a detailed modelling space that can be applied to other swarm intelligence contexts. In fact, explaining this goal-orientated ontology and presenting its design can propel related application-specific modelling.

5.1. Contributions

Three contributions characterize this study as follows:

- The paper presented a formal understanding of the key entities key in the design of an SS-bot ontology. This literature extends content.
- This work gives a baseline upon which other studies aimed at understanding knowledge representation in other swarm contexts will be built. Representing swarm knowledge in the form of an ontology creates the building blocks for heterogeneous swarm ontologies.
- Although the focus was on understanding the elements of an ontology for coordinating homogeneous SS-bots, the work presents a new method for describing swarm systems.

5.2. Future Work

Four ambitious directions for future work noted as follows:

- An experiment to corroborate this knowledge representation approach is pending.
- The SS-bot ontology could be extended by incorporating applicable knowledge domain to cover certain use cases. Precisely, the SS-bot ontology should be assessed further for applicability, extensibility, and expandability.
- Integrating the SS-bot ontology with other swarm intelligence ontologies to, eventually, create a heterogeneity is pending.
- More knowledge domains can be considered for the SS-bot ontology to include mission planning under uncertainty, dealing with incomplete data, managing vague, inaccurate, inconsistent, and imprecise situations.

Acknowledgments

We acknowledge the moral and technical support given by the Sol Plaatje University, Department of Computer Science, Data Science, and Information Technology. This research was funded through the CAIR project (Centre for Artificial Intelligence Research) grant, with the grant 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).

6. References

Abosaif, A.N. & Elrofai, S.E. (2020). An Efficient QoS-aware Services Selection in IoT using A Reputation Improved- Social Spider Optimization Algorithm. Research Square, https://doi.org/10.21203/rs.3.rs-38596/v2.

Aggarwal, S., Chatterjee, P., Bhagat, J., Purbey, K. K. & Nanda, S. J. (2017). Social Spider Optimization Algorithm with Chaotic Initialization for Robust Clustering. Dept of Electronics and Communication Engineering, Malaviya National Institute of Technology, India.

Bas, E. & Ulker, E. (2021). Comparison between SSA and SSO algorithm inspired in the behavior of the social spider for constrained optimization. AI Review, Vol 54:5583-5631. https://doi.org/ 10.1007/s10462-021-10035-x.

Bock, J. (2013). Ontology Alignment Using Biologically Inspired Optimization Algorithm. Doctoral Thesis. KIT Scientific Pub.

Bourjot, C. & Chevrier, V. (2001). Multi-Agent Simulation in Biology: Application to Social spider case. Proceedings of Agent Based Simulation Workshop II, Passau, Germany, Lecture notes in Computer Science.

Carrillo-Zapata, D., Milner, E., Hird, J., Tzoumas, G., Vardanega, P. J., Sooriyabandara, M., Giuliani, M., Winfield, A. F. T. & Hauert, S. (2020). Mutual Shaping in Swarm Robotics: User Studies in Fire and Rescue, Storage Organization, and Bridge Inspection. Frontiers in Robotics & AI, Vol 7:53. doi:10.3389/frobt.2020. 00053.

Cheraghu, R.A., Shahzad, S. & Graffi, K. (2021). Past, Present, and the Future of Swarm Robotics. arXiv:2101.00671v1 [cs.RO].

Cuevas, E., Cienfuegos, M., Zaldívar, D. & Pérez-Cisneros, M. (2013). A swarm optimization algorithm inspired in the behavior of the social spider. Expert systems with application, Vol 40:16, 6374– 6384.

Evangeline, D. & Abirami, T. (2019). Social Spider Optimization Algorithm: Theory and its Applications. Int. Journal of Innovative Technology and Exploring Engineering, Vol 8(10).

Farshi, T.R. & Orujpour, M. (2019). Multi-level image thresholding based on social spider algorithm for global optimization. Int. Journal of Information Technology, Vol 11:713–718.

James, J.Q.Y & Victor, O.K.L. (2015). A Social Spider Algorithm for Global Optimization. arXiv:1502.02407v1 [cs.NE].

Kamath, A., Primavera, S.D., Wright, C.M., Doering, G.N., Sheehy, K.A., Pinter-Wollman, N. & Pruitta, J.N. (2018). Collective behavior & colony persistence of social spiders depends on their physical environment. Behavioral Ecology, Vol 30:1, 39–47. doi:10.1093/beheco/ary158.

Li, X., Bilbao, S., Martín-Wanton, T., Bastos, J. & Rodriguez, J. (2017). SWARMs Ontology: A Common Information Model for the Cooperation of Underwater Robots. Sensors, Vol 17(3), 569. https://doi.org/10.3390/s17030569

Melanie, S., Martina, U., Micha, S. & Wilfried, E. (2020). Swarm Robotic Behaviors and Current Applications. Frontiers in Robotics and AI, Vol 7:53. doi:10.3389/frobt.2020.00053.

ISBN: 978-99949-0-888-2

Navarro, I. & Matía, F. (2013). An Introduction to Swarm Robotics. Int. Scholarly Research Notices. doi.org/10.5402/2013/608164.

Oliveira, M., Pinheiro, D., Macedo, M., Bastos-Filho. & Menezes, R. (2020). Uncovering the social interaction network in swarm intelligence algorithms. Applied Network Science, Vol 5, Article Number 24. https://doi.org/10.1007/s41109-020-00260-8

Otor, S. U., Akinyemi, B. D., Aladesanmi, T. A., Aderounmu, G. A. & Kamagate, B. H. (2019). An adaptive bio-inspired optimization model based on the foraging behaviour of a social spider. Cogent Engineering, Vol 6:1, 1588681. doi: 10.1080/23311916.2019.1588681.

Perez, J.A., Deligianni, F., Ravi, D. & Guang-Zhong, Y. (2016). Artificial Intelligence and Robotics. UK – RAS Network. Robotics and Autonomous systems. Imperial College London.

Sadik, U. & Urlker, E. D. (2014). Application of Particle Swarm Optimization to Microwave Tapered Microstrip Lines. Computer Science & Engineering: Int. Journal, Vol 4(1).

Saffre, F., Furey, R., Krafft, B. & Deneubourg, L. (1999). Collective Decision-making in Social Spiders: Dragline-mediated Amplification Process Acts as a Recruitment Mechanism. Journal of Theoretical Biology, Vol 198, 507-517.

Shukla, U.P. & Nanda, S.J. (2019). Dynamic clustering with binary social spider algorithm for streaming dataset. Springer - Soft Computing, Vol 23, 10717–10737.

Srikanth, K. & Sridhar, L. (2020). Continuum Robots for Manipulation Applications: A Survey. Journal of Robotics, Vol 2020. https://doi.org/10.1155/2020/4187048

St-Onge, D., Varadharajan, V.S., Švogor, I. & Beltrame, G. (2020). From Design to Deployment: Decentralized Coordination of Heterogeneous Robotic Teams. Frontiers in Robotics and AI, Vol 7:53. doi:10.3389/frobt.2020. 00053.

Tan, Y. & Zheng, Z. (2013). Research Advance in Swarm Robotics. Defense Tech, Vol 9:18-39.

Tawhid, M.A. & Ali, A.F. (2016). A simplex social spider algorithm for solving integer programming and minimax problems. Memetic Computing, Vol 8, 169–188.

Thalamala, R. C., Reddy, A. V. & Janet, B. (2020). A Novel Bio-Inspired Algorithm Based on Social Spiders for Improving Performance and Efficiency of Data Clustering. Journal for Intelligent Systems, Vol 29 (1): 311–326.

Wignall, A. E. & Herberstein. M. (2013). The Influence of Vibratory Courtship on Female Mating Behaviour in Orb-Web Spiders. PLOS One, Vol 8(1). http://doi.org/10.1371/journal.pone.0053057

Xavier, V.M.A. & Annadurai, S. (2020). Chaotic social spider algorithm for load balance aware task scheduling in cloud computing. Cluster Computing, Vol 22, S287–S297.

Zhao, L., Han, L. & Ping, Z. (2019). Diversity-enhanced particle swarm optimization algorithm based on the group behaviour of social spiders. Engineering Optimization, Vol 53(5), 811–829. doi:10.1080/0305215X.2020.1754407.

Zhaoyu, Z., Ortega, J.M., Martínez, N.L., Castillejo. P.A. (2020). Rule-Based Reasoner for Underwater Robots Using OWL and SWR. Sensors, Vol 18(10), 3481. https://doi.org/10.3390/s18103481