EPiC Series in Education Science
Volume 4, 2022, Pages 31–41
Proceedings of NEMISA Summit and Colloquium 2022: The Future of Work and Digital Skills

A Catalogue of Robotic Device Actions for Creating Swarm Intelligence Ontologies

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Abstract

Efforts to synchronize mobile robotic devices into desired formation are a niche research area. Most tips for programming plausible swarm intelligence are discretely taken from mathematics, physics, biology, chemistry, or nature. However, integration of the different cues into useful swarm intelligence systems is challenging. The notion of swarm intelligence ontologies is compelling. It captures theories, rules, policies, and meta-information about the creation of practical swarm systems. Swarm intelligence ontologies can establish the relationships between different swarm modelling paradigms to bring about generality. Such generality requires us to review various forms of swarm intelligence systems seeking to understand simulated robotic device actions that give rise to emergent behaviour. Two arms of such robotic device actions are noted. One set of robotic device actions are non-interactive. These actions are mainly taken from mathematics, physics laws, or other elitist methods. On the other hand, there are robotic devices actions regarded as interactive. Commonly, interactive robotic devices are bio-inspired. This article sequentially discusses these two categories of robotic device actions towards building a catalogue of actions to inspire the creation of swarm intelligence ontologies. Notably, most non-interactive robotic devices have abilities to recall the paths they previously followed. In other cases, robotic devices can use some form of language to share directional cues. However, the bulky of the literature points to robotic devices that can follow chemical tips towards the targets. A very small chunk of non-interactive robotic devices can rely on geometry, calculus, forces, beacons, or landmarks to orientate. Some interactive robotic devices can explicitly message pass. Some use environment mediated interactions. The type of data shared between such robotic devices is usually overtly connoted, including stacks, vectors, chemicals, forces, landmarks, or beacons. That way, the key robotic devices actions at individual level are apparently associated with reading stacks, interpreting language verbs, detecting chemicals, self-localizing, motion planning, or finding directions. This specificity in the characteristics of robotic device actions is the basis for the design of the swarm intelligence ontologies we envision.

1 Introduction

Understanding the mechanisms in which simulated robotic devices in swarms converge on emergent behaviour is an epic task (Chibaya: PhD thesis, 2014). In this case, emergent behaviour is the degree to which we see features at swarm level that cannot be accounted for at individual robotic device level (Fisher & Lipson: article, 1999). It implicitly defines the synergy by the robotic devices (Sato & Matsuoka: article, 2009; Stepney et al.: article, 2007). Grasping the main concepts, rules, and processes through which simulated robotic devices are synchronized into forming emergent behaviour is the key ingredient for defining catalogues of actions that can inspire the design of useful swarm intelligence ontologies. Generally, an ontology captures the key aspects in a nominated knowledge domain, along with their relationships. In this article, we primarily identify the actions of simulated robotic devices which trigger emergent behaviour with the hope to suggest the building blocks of swarm intelligence ontologies. In our view, a concise swarm intelligence ontology should emanate from integrated views built on the actions of different categories of simulated robotic devices. That specificity in the understanding of robotic device actions at individual level is pivotal to fruitful conceptualization and appropriate recommendation of those actions for the design of desired swarm intelligence ontologies.

Two categories of simulated robotic device actions are distinguished in this work. On one hand, there are robotic device actions regarded as non-interactive. Other robotic device actions are interactive. In this case, non-interactive actions are dominantly mathematics-based, physics-driven, or elitist. Contrary, interactive actions are bio-inspired (Chibaya: PhD thesis, 2014). In swotting each category, we emphasize an understanding of the procedures underpinning robotic device control, communication, and orientation.

1.1 Problem statement

We seek to understand the different forms of simulated robotic device actions which cause emergent behaviour under different circumstances and prescribe those actions as building blocks of useful swarm intelligence ontologies. An understanding and appropriate consideration of those actions in the design of swarm intelligence ontologies may, potentially, create baseline platforms upon which practical swarm intelligence inspired solutions to real-life problems may ensue.

1.2 Overview

The rest of the article proceeds as follows: section 2 presents a discussion on non-interactive robotic device actions, distinguishing between mathematics-based, physicomimetic, and elitist actions. Section 3 presents a discussion on interactive actions, focusing on the actions that characterize one-on-one interactions, as well as those actions that portray indirectly mediated interactions. In section 4, we discuss how those actions fit into the swarm intelligence ontology design problem. The conclusion follows in section 5, highlighting the key observations, contributions, and the direction for future work.

2 Non-Interactive Robotic Device Actions

Non-interactive actions are mainly mathematical, physicomimetic, or elitist. The actions of robotic devices in this category, including movement, are built on geometric equations, vectors, forces, or matrices. Related robotic devices are characterized by large memories (Ngo et al.: article, 2005) in which to keep formulae (Monte De Oca et al.: article, 2005), positions of objects (Mullen et al.: article, 2009), vectors (Wu et al.: article, 2005) or information about the landmarks in the environment (Wehner et al.: article, 2006). However, different forms of non-interactive actions are contemplated to have their own pertinency and peculiarities as separately discussed in the three subsequent subsections.

2.1 Mathematical Actions

Robotic devices that rely on actions characterized as mathematical perform rigorous computations using prescribed formulae to define robotic device communication, orientation, and movement policies (Ngo et al.: article, 2005). The popular branch of mathematics involved is geometry and calculus.

Geometry-inspired robotic devices do not require any direct interactions with one another. Rather, each robotic device's positional preferences are based on the Cartesian geometry of its location (Trofimova et al.: article, 1998). Also, these robotic devices self-localize relative to the positions of specific objects in the environment (Trofimova et al.: article, 1998). The independent calculations each robotic device performs define communication while instigating orientation and triggering mobility. Some calculations are about measuring distances to targets or estimating the angles of robotic device rotation relative to specific objects in the environment (Ngo et al.: article, 2005). Motion is also overseen using velocity profiles and collision avoidance schemes.

On the other hand, calculus-based robotic devices calculate movement trajectories using globally perceived features of the environment (Sarfati: article, 2007). They self-localize using pure mathematics or, sometimes, Jacobian matrices (Harris: article, 2007). In both cases, emergent behaviour arises from robotic devices' individual abilities to follow the mathematics laws thereof (Ngo et al.: article, 2005).

However, the demand for robotic devices' ability to solve equations and calibrate mathematical functions into directional information is heft, inflexible, and lacks the desired robotic device autonomy. That requirement for robotic devices' ability to generate local coordinate systems in which to self-localize is computationally savvy. Robotic devices with large memory are structurally sophisticated. The robotic device naivety envisioned in most swarm intelligence systems is compromised, especially when robotic devices can calculate velocities, distances, and orientation angles. With the desired simplicity in the design of robotic devices, some of the mathematical actions described here are detrimental to the flexibility we anticipate ontology-based swarms.

2.2 Physicomimetic Actions

Physicomimetic actions imitate physics laws. For example, a robotic device in this category would remain at rest unless some force acts on it. If in motion, it would remain in motion at a constant speed unless acted on by an unbalanced force. Acceleration or deceleration depends on the amount of the forces applied. When a robotic device exerts some force to another, that other robotic device would exert an equal opposite force. Three classes of physicomimetic actions are noticed, namely, forces-based, mechanical, and hybrid actions.

Forces-based actions rely on the sensitivity of robotic devices to other robotic devices in their proximity (Balch & Arkin: article, 1999). Robotic devices can attract and repel one another (Azzag et al.: article, 2007). Movement speed and orientation are regulated using the push and pull effects (Bayazit et al.: article, 2005), thus defining robotic device positional preferences (Lua: article, 2005). Typical examples of forces-based actions are seen in (Spears et al.: article, 2005). Often, the main causes of emergent behaviour are robotic devices' sensory skills. Precisely, the potential field of energy that develops around each robotic device is the key ingredient to subsequent swarm actions.

Mechanically inspired robotic devices are propelled using physically mounted electric motors. Orientation and subsequent movement trajectories are pre-defined in motion firmware installed in the robotic devices. These electric motors are often built with enough energy to run for the duration of the task (Paulson: article, 2008). However, pre-programmed outcomes often arise instead of emergent behaviour. Besides, robotic devices should be deployed in specific densities, where each robotic device has a well-defined schedule of tasks to accomplish (Paulson: article, 2008).

Hybrid actions combine the features of forces-driven and mechanical robotic devices. Typical hybrid robotic devices are inferred in (Pelechano et al.: article, 2007) where, both virtual forces and geometric rules are put together to trigger swarm navigation. In their case, displacement equations are used when the robotic device's sensory abilities detect obstacles. Nevertheless, integration of different robotic device skills does not take away the complexities associated with each skill considered. Rather, more special cases may be required in the motion schemes thereto (Pelechano et al.: article, 2007).

Although physicomimetic actions are plausible, we anticipate robotic devices that are more nature inclined because of the robustness, fault tolerance, scalability, and the flexibility that ensue in natural swarms. Like the mathematical counterparts, physicomimetic actions take away robotic device autonomy. Individual robotic device behaviours are seemingly regulated by the density of attractive and repulsive counterparts in the swarm (Cao et al.: article, 1997). Worse still, the requirement to physically mount sensory devices on each robotic device is expensive. Thus, swarm intelligence ontologies built on physicomimetic views remain unrealistic.

2.3 Elitist Actions

Elitist actions give robotic devices super-intelligence. Related robotic devices are designed with sufficient memories to recall past experiences. They can use recall to infer future actions. In addition, elitist robotic devices can share information. Some robotic devices in this group can recall entire path maps (Mullen et al.: article, 2009), while others rely on landmarks and beacons in the environment to trigger future actions (Wehner et al.: article, 2006).

Path recalling robotic devices can selectively choose the control mechanisms to employ at a time. Sometimes, they may recall the paths from the landmarks around (Sudd: article, 1960). In other cases, they may recall what to do next from the behaviour of their neighbours (Sudd: article, 1960). When isolated, these robotic devices can use the direction and angle of the sun to orientate (Koichi & Mari: article, 1996). There are cases where these robotic devices can recall other robotic devices' identities (Sheeham & Tibbetts: article, 2008), steering one-on-one cooperation. Desert ants, for example, are elitist since emergent behaviour emanates without neither direct nor indirect interactions. Orientate is achieved using other environment features, including sensory hints (Cavalcanti et al.: article, 2006) and random movements (Jackson et al.: article, 2004). Elitist robotic devices, therefore, frequently updated their knowledge until deterministic emergent behaviour arises (Dhariwal et al.: article, 2004).

Nonetheless, robotic devices that can recall things require unlimited memory (Wehner et al.: article, 2006). Although the landmarks provide direction vectors and orientation information to elitist robotic devices (Wu et al.: article, 2005), the implicit computational demands thereof are undesirable. Also, elitism eliminates robotic device autonomy. These features are not convincing in the design of swarm intelligence ontologies.

3 Interactive Robotic Device Actions

Interactive actions are predominantly nature inspired. They are mainly modelled on the behaviours of natural groups such as cells (Xi et al.: article, 2005), birds (Reynolds: article, 1987), DNA (Reif: article, 2002), bees (Reynolds: article, 1987), or ants (Chibaya & Bangay: article, 2007) or spiders. In this case, robotic devices depend on one another to complete individual-level tasks. Interactions are local. In one group, interactions are one-on-one. In another class, robotic device interactions are indirectly mediated via the environment.

3.1 Actions of Robotic Devices that can Interact One-on-One

In this category, robotic devices are commonly modelled with the ability to exchange information one-on-one. They often share memory blocks with directional data (Nasipuri & Li: article, 2002), path history (Nasipuri & Li: article, 2002), or data about the positions of some objects (Monte De Oca et al.: article, 2005). In some cases, robotic devices can explicitly share calls in specific languages

(Rajbhupinder et al.: article, 2010; Nagpal et al.: article, 2010). However, the key consideration in all cases pertains to the requirement to know the type of data shared, how and when it is shared (Haasdijk et al.: article, 2013). Consequently, three types of robotic devices are distinguished in this category.

One group shares path history. In these, stack-like message blocks are hopped from one robotic device to another (Trianni & Dorigo: article, 2005). These stacks usually record coordinates of the paths previously used (Nasipuri & Li: article, 2002) or data relating to the best routes followed earlier (Hara et al.: article, 2005). Other stacks record entire paths maps (Monte De Oca et al.: article, 2005). Usually, a learning framework arises (Lien et al.: article, 2005) where the experiences of other robotic devices are learnt by referencing their stacks. The learning robotic devices can create their own paths maps from the learnt experiences (Bayazit et al.: article, 2005; Rodriguez et al.: article, 2007).

Robotic devices that can share geometric vectors are more promising. They do not require excessive memory capacities since they would only keep specific vector components (Nasipuri & Li: article, 2002). Sometimes, the vectors shared interpret pheromone levels. In other cases, these vectors interpret the geometries of specific objects (Nasipuri & Li: article, 2002).

Robotic devices in which some form of a communication language ensues are also visible. Most robotic device communication languages are developed with verbs, vocabulary, syntax, and semantics (Rajbhupinder et al.: article, 2010). The growing point and origami shape theories (Nagpal et al.: article, 2010) is a more popular language in this category. The work of (Butera: PhD thesis, 2002) is also fascinating, where a growing point language was used to implicitly enhance pheromone dissipation. Other robotic device languages rely on high-level description of functions and relationships among the robotic devices. Such languages coordinate the behaviour of robotic devices throughout (Stefano & Santoro: article, 2001). In most cases, pre-programmed coordination laws are incorporated upfront, together with the vocabulary thereof (Nagpal et al.: article, 2010). A few other languages support call protocols explicitly developed into verbs (Cao et al.: article, 1997; Beal: article, 2005). A robotic device communication language based on geometric primitives was also used as an amorphous medium language (Beal: article, 2005). In their works, the language described behaviour in terms of spatial regions of the amorphous media (Nagpal et al.: article, 2010), where neighbours only communicated utilizing a shared memory region. However, such calls are, often, broadcast to the entire swarm, compromising robotic device privacy and autonomy.

Investigations aimed at identifying the primitive actions of ant-like agent with abilities to explicitly communicate using a language were also administered. However, the language remained very limited in vocabulary (Rajbhupinder et al.: article, 2010). Only a limited domain of emergent behaviour can be achieved using the language. Attempts to propose robotic devices that can use sentence messages have been in progress for a while (Dastani et al.: article, 2003). The results presented, so far, lack in that the roles of receiver robotic devices are made consequences of the desires of communicating robotic devices (Naeem et al.: article, 2007). In other words, the independence of the receiver robotic device is grossly compromised. Nonetheless, these debates are ongoing and bringing us closer to the design of the desired swarm intelligence ontologies.

Although the notion of sharing information is nature-inspired (Nouyan & Dorigo: article, 2007), three disadvantages emanate in this category. First, robotic devices should possess good memory capacities to hold the shared message blocks. Also, their memory structures should be compatible with the message blocks shared. Thus, all robotic devices should be structurally similar (Caicedo et al.: article, 2007) so that they can share homogeneous content. More so, the information held in less successful robotic devices may be lost when the path histories of relatively successful robotic devices are preferred. That alone expediates data loss at swarm level. These needs are perturbing in the design of practical swarm intelligence ontologies.

3.2 Actions of Robotic Devices that rely on Mediated Interactions

Swarm control models where robotic devices' interactions are indirectly mediated are mostly chemistry or biologically inspired. For example, virtual chemicals can be placed on the environment to create shared memories for the swarm. These chemicals are either placed on the environment by objects or by the robotic devices themselves (Dorigo et al.: article, 1996). Models where objects deposit chemicals on the environment are referred to as optimized. Contrary, those models in which the robotic devices excrete chemicals are referred to as stigmergic.

Optimized models use path markers such as plume gradients (Dhariwal et al.: article, 2004). Robotic devices can self-localize relative to the chemical sources (Colin: article, 2006). Local coordinate systems arise from robotic devices' perception of the quality of chemicals around them (Ravary et al.: article, 2007). In most cases, these chemicals define unidirectional paths (Jackson et al.: article, 2004). Elitist mechanisms are needed when multi-directional paths are required (Koichi & Mari: article, 1996). A common form of elitism involves robotic devices that can conveniently switch between different interaction strategies (Monte De Oca et al.: article, 2005) such as using sensory cues together with chemical gradients (Wehner et al.: article, 2006). In other cases, robotic devices can have limited vision to augment chemical tracing (Healey & Pratt: article, 2008). However, the bulk of robotic devices supplement chemical tracing with recall (Di Caro et al.: article, 2008; Negulescu et al.: article, 2006). However, elitism is not desirable in swarm intelligence because it takes away agent autonomy (Yang & Zhuang: article, 2010)

Stigmergic robotic devices excrete specific levels of pheromones (Dorigo et al.: article, 1996; Merkle et al.: article, 2006). Stigmergy is a non-symbolic form of communication mediated via the environment (Socha: article, 2008; Parunak: article, 2005). It captures the notion that robotic devices' activities mark signs on the environment which determine subsequent actions (Shell: article, 2003). Two types of stigmergic robotic devices are observed (Burgess: article, 2009). Sematectonic robotic devices (Shell: article, 2003) can change the physical characteristics of the environment. Examples of these are hole making robotic devices (Ghaiebi & Solimanpur: article, 2007), pit constructing robotic devices (Montgomery et al.: article, 2007), or nest building robotic devices (Aleksiev et al.: article, 2007). On the other hand, sign-based robotic devices mark pheromone signs on the environment. These pheromones indirectly influence subsequent robotic device behaviour, including task related behaviour.

In sign-based robotic devices, mobility is probabilistic (Chibaya & Bangay: article, 2007). Path selection is based on the levels of pheromones held around a robotic device. Three sub-classes of sign-based robotic devices are noted, including single pheromone users, two pheromone users, and multiple pheromone users. Single pheromone users can excrete and perceive one and only one form of pheromone. The source of that single pheromone are the robotic devices (Dorigo et al.: article, 1996). However, there are cases where the targets or other objects have been used to also place single pheromone on the environment (Cavalcanti et al.: article, 2006). Those abilities, however, are seen as elitist. The most popular single pheromone model is the double bridge scenario (Dorigo et al.: article, 1996; Solimanpur et al.: article, 2005). In this case, gradients emerged in which robotic devices favoured movements towards higher concentration of pheromone. However, again, elitist strategies are required when bi-directional paths are sought (Koichi & Mari: article, 1996).

Scenarios where robotic devices use two forms of pheromone minimize elitism. These two levels of pheromones are excreted by the robotic devices and can co-exist (Alcala et al.: article, 2001). Often, one level of pheromone is excreted when robotic devices search for targets, and another level is dropped after they find the target (Chibaya & Bangay: article, 2007). Also, there are cases where one or both levels of pheromones originated from other objects in the environment (Engle & Whalen: article, 2003).

Cases where multiple levels of pheromone are supported have also been noted. Multiple levels of pheromone remedy most flaws noted in optimized, single pheromone, and two pheromone models. Thus, relatively robust, fault-tolerant, flexible, scalable, and adaptive models arise (Cavalcanti et al.: article, 2006). Several examples of multiple pheromone systems are observed in medical scenarios

(Cavalcanti et al.: article, 2006). A major setback for most multiple pheromone models is that the sources of these levels of pheromones are, often, some objects in the environment, purporting elitism (Yang & Zhuang: article, 2010), where robotic devices can selectively distinguish between the meanings of different levels of pheromone (Engle & Whalen: article, 2003). In designing the envisioned swarm intelligence ontologies, we seek naivety, freedom, and autonomy of robotic devices. The key information should be held externally (in the environment) so that errors at robotic device level do not affect task completion at swarm levels.

4 Discussions

A distinction between non-interactive and interactive robotic devices action was presented. Emphasis was put on the characteristics, pros, and cons of the various actions, whether direct or indirect. Different classes of robotic devices actions were considered, including path recalling, geometric, language-based, optimized, stigmergic, calculus-based, forces driven, mechanical, hybrid, or beacon and landmarks-based actions. Similarly, different communication strategies prevalently inferred in the literature were noted, including direct message passing, environment mediated, sensor-based, vision, or hybrid mechanisms. We discussed the different forms of data shared between robotic devices, where possible, to include stacks, vectors, chemicals, forces, landmarks, or beacons. Swarm properties related to robotic device orientation strategies were also summarized into vector-based, language-based, probabilistic, calculated directions, forces based, or cues steered by landmarks. As a result, the key robotic device activities at individual levels were connoted and pinpointed as reading stacks, detecting chemicals, interpreting language verbs, self-localizing, motion planning, or calculating directions. The key parameters of emergence that characterize each class of robotic devices were identified as robotic device memory, elitism, robotic device abilities, the environment, laws of motion, and communication mechanisms. In our views, the design of useful generic swarm intelligence ontologies should capture all these aspects holistically. Figure 1 summarizes a catalogue of robotic device actions for creating swarm intelligence ontologies.

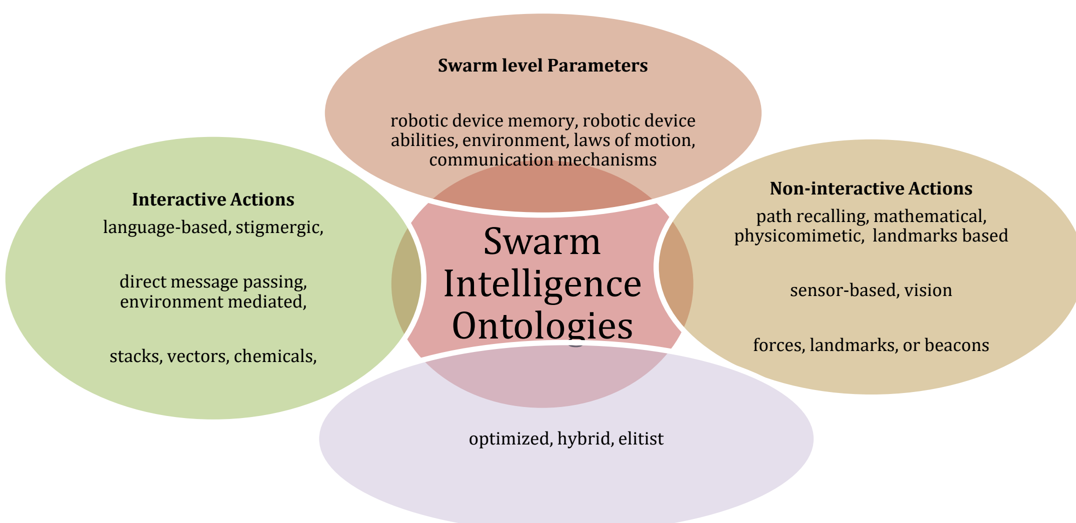

Figure 1: A catalogue of robotic device actions for creating swarm intelligence ontologies

5 Conclusion

The following four observations arise:

- Generally, desired swarm intelligence ontologies should comprise the knowledge domain related to robotic device design, self-localization, orientation, and movement policies as the key ingredients for synchronized activities. In this case, orientation should be guided by some form of meta-information around the robotic devices such as sensory skills or memories. On the other hand, movement is triggered by specific displacement factors such as attraction and repulsion effects. Thus, robotic device self-localization, orientation, and movement abilities are apparent indispensable policies to consider.
- Robotic devices mainly rely on locally perceived information, be they forces, equations, geometry, sensory factors, chemicals, or other robotic devices. This information is regularly updated. Swarm intelligence ontologies should consider appropriate system update rules. It should dictate how much levels of pheromones are dropped, how much pheromone levels evaporation or diffusion, the vector modulation policies, how targets are detected, and how vectors are normalized.
- Robotic devices require some basic memory in which to store internal state information. Swarm intelligence ontologies should present policies for appropriate architectural design of robotic devices such that they are able to handle the data presented in the system.
- Although robotic devices should remain naïve and autonomous throughout, interactivity brings about some desirable learning framework (Haasdijk et al.: article, 2013) - both at individual and swarm levels - in which robotic devices collectively engineer solutions based on some shared knowledge. Interactivity is fascinating, not because it brings about intelligent individuals, but because, collectively, robotic devices yield robust and fault tolerant emergent behaviour. Additionally, it brings stable solutions from very simple and naïve actions. Swarm intelligence ontologies should incorporate apt learning frameworks for these same benefits.

The value of this work is emphasized by two contributions as follows:

- The categorization of robotic device actions creates a basis for identifying the vocabulary, verbs, grammar (syntax), and semantics (meanings) of the desired swarm intelligence ontologies. In our views, flawless designs will likely capture swarm knowledge spaces that expands the scope of applications that can be developed through swarm intelligence perspectives.
- Aspects related to quantification of emergent behaviour are invisible in the literature. It is a gap that needs to be pursued before we can create complete swarm intelligence ontologies. This observation creates a new research avenue.

Three potential directions for future works are as follows:

- Although robotic devices actions have been discussed, logical and physical designs of the much-awaited swarm intelligence ontologies are overdue.
- An understanding of the metrics that can be used to quantify the emergent behaviour yield from using swarm intelligence ontologies is apparently required.
- An explicit study of the pros and cons of each robotic device action, the contribution each action makes to emergent behaviour, and how this contribution can be measured under different circumstances will create new content in this body of knowledge.
- Development of practical applications based on the envisioned swarm intelligence ontologies is also belated.

Acknowledgements

This article was funded through the CAIR (Centre for Artificial Intelligence Research) grant agreement number: CSIR/BEI/HNP/CAIR/2020/10, supported by the Department of Science and Innovation (DSI), South Africa. We are grateful for the mentorship given by colleagues in the Computer Science Department, University of Cape Town.

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