ISSN: 2090-4908
International Journal of Swarm Intelligence and Evolutionary Computation

OPEN ACCESS Freely available online

Review Article

Potential Building Blocks for the Creation of Generic Swarm Intelligence Ontologies

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ABSTRACT

Swarm Intelligence Ontology (SIO) captures concepts, policies, rules, and processes within a specific swarm intelligence domain. It sets the relationships between the concepts, policies, rules, and the processes of a swarm intelligence model to visualize interconnections. To create a generic SIO, a deep understanding of probable building blocks from various inspiring swarm control models is required. Precisely, meticulous comprehension of how swarms of robotic devices are designed, configured, and coordinated is apparently required. Two arms of prospective building blocks for creating generic SIOs are identified in the literature.

On the one hand, non-interactive swarm control models are prevalent, consisting of mathematics-based, physics-inspired, and elitist robotic devices. On the other hand, interactive swarm control models dominate, commonly built on natural colonies. This review describes the likely building blocks for creating generic SIOs inspired by these two categories of swarm control systems.

Keywords: Swarm Intelligence Ontology (SIO); Robotic device; Swarm control model; Non-interactive swarm control models; Interactive swarm control models; Emergent behavior

INTRODUCTION

Understanding the different ways in which robotic devices in swarms are designed, configured, and coordinated towards emergent behaviour is an epic task [1]. In this context, emergent behaviour is the degree to which we see features at swarm level, emanating from the individual actions of the members of the swarm [2,3]. It defines the synergy of the robotic devices in a swarm [4-7]. Grasping the concepts, policies, rules, and processes which cause emergent behavior in different swarm intelligence systems is the main recipe for proposing Swarm Intelligence Ontologies (SIOs). This review seeks to establish the actions of robotic devices in different swarms which contribute to emergent behaviour at swarm level towards prescribing generic SIOs.

SIOs capture the concepts, policies, rules, and processes of a swarm and establish the relationships between them while also visualizing how they are connected. Building a generic SIO requires an understanding of the domain in which the SIO will serve. A proper SIO can emanate from a comprehensive review of different swarm control models. Identification of the basis of emergent behaviour in different swarm contexts and understanding the discrete actions of robotic devices in the swarms, which caused emergent behaviour in different scenarios [8], as well as pinpointing how those actions were interpreted into useful robotic device cues, pose challenges. The goal is to isolate discrete aspects of swarms that cause emergent behaviour in different scenarios and use those as prospective building blocks for creating generic SIOs.

Two classes of inspiring swarm control models are distinguished. On the one hand, non-interactive swarm control systems comprised of mathematics-based, physics-based, and elitist robotic devices are prevalent. On the other hand, interactive swarm control systems commonly built on natural colonies [1] are dominant. In swotting each category, we emphasize the control mechanism inferred, the underpinning theory, and all the communication considerations embraced. Commonalities are pinpointed with the hope of, in the end, prescribing a

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Received: 30-Mar-2022, Manuscript No. SIEC-22-15988; **Editor assigned:** 01-Apr-2022, Pre QC No. SIEC-22-15988 (PQ); **Reviewed:** 15-Apr-2022, QC No SIEC-22-15988; **Revised:** 22-Apr-2022, Manuscript No. SIEC-22-15988 (R); **Published:** 02-May-2022, DOI: 10.35248/2090-4908.22.11.247.

Citation: Chibaya C (2022) Potential Building Blocks for the Creation of Generic Swarm Intelligence Ontologies. Int J Swarm Evol Comput. 11:247.

general concise methodology for characterizing Swarm Intelligence Principles (SIO).

Section 2 describes non-interactive swarm control models, while section 3 dwells on interactive swarm control systems. Conclusions are drawn in section 4, highlighting the key prospective components of the proposed SIO, the contributions of the review, as well as pinpointing the potential direction for future work.

PROSPECTIVE BUILDING BLOCKS OF SIOS INSPIRED BY NON-INTERACTIVE ROBOTIC DEVICES

Non-interactive swarm control systems are commonly modelled using mathematics and the physics laws of motion. The movement trajectories of robotic devices in this category are commonly defined using equations, vectors, and matrices. The robotic devices thereof are characterized by large storage capacities to keep positions of objects vectors and information about the landmarks in the environment [9-14].

There are three types of non-interactive robotic devices noted in this study. The first group comprises mathematically driven robotic devices. Another set uses physics-based principles. The last chunk fall under the elitist category. Each type possesses unique control rules, pertinent communication policies, particular orientation methods, and exclusive movement cues.

Mathematically driven robotic devices

Robotic devices in this group rely on rigorous mathematical computations to function. Mathematical formulae are used to define orientation and movement policies [9]. Two branches of mathematics (geometry and calculus) are used for this purpose.

Geometry-inspired robotic devices neither require direct nor indirect interactions among themselves. Rather, each robotic device's positional preferences are based on the Cartesian geometry of its location in the environment [15]. These robotic devices have computational abilities to self-localize relative to the positions of specific objects in the environment. They perform independent calculations out of which they can orientate, measure their distances to targets, and estimate the angles to turn relative to specific objects in the environment [9]. Motion is handled using velocity profiles and collision avoidance schemes. The main causes of emergent behaviour are the robotic devices' memories, their individual abilities, and the mathematics laws used in the geometry theory [9].

Many disadvantages are noted in geometry-inspired robotic devices. First, the requirement to be computationally savvy, abilities to generate local coordinate systems in which to self-localize, and the demand for large memory purport sophisticated robotic devices. In addition, the environmental features that steer robotic device actions, as well as the need for robotic devices to be able to calculate velocities, distances, orientation angles, and define movement and collision avoidance profiles are too complicated and sophisticated for inclusion in the design of practical SIOs.

Calculus-inspired robotic devices, on the other hand, can calculate movement trajectories based on the relative positions of globally perceived objects in the environment [16]. The main activity of every robotic device in this group is to self-localize. Jacobian matrices have also been successfully utilized to achieve self-localization in swarms [17]. However, that demand for extra abilities to solve equations and calibrate mathematical functions into directional information is heft for inclusion in the design of generic SIOs. In fact, these robotic devices lack the desired flexibility and autonomy to emulate nature.

Physics bases robotic devices

Physics-inspired robotic devices use laws of motion to orientate. Three sub-classes of robotic devices are noted in this category, namely, forces-based, mechanical-based, and hybrid robotic devices.

Forces-based robotic devices can respond to in-built virtual forces for sensing their proximity to others [18,19]. These robotic devices can attract or repel others depending on their distances apart [20,21]. Movement speed and orientation are regulated using the push and pull effects from the virtual forces exerted between the neighbours [22,23], thus defining positional and the directional preferences of each robotic device [24,25]. Typical examples of forces-based robotic devices are connoted in [26-28], where it is shown how robotic devices can self-organize into mobile hexagonal lattices moving towards some target. The main causes of emergent behaviour, in this case, are the sensory skills of robotic devices.

Precisely, the potential fields of energy that develop around robotic device are the key contributors to subsequent swarm actions. However, robotic devices in this class lack autonomy. Their behaviour relies on the density of the attractive and repulsive counterparts [29]. Worse still, these robotic devices should have sensory devices mounted onto them. These requirements are unattractive for the design of generic SIOs.

Mechanically inspired robotic devices, on the other hand, are commonly propelled using electric motors physically mounted onto each. Orientation and subsequent movement trajectories are pre-defined in the motion firmware routines.

The electric motors are often built with enough energy to run for the duration of the task [30]. However, swarms in this category prevalently create pre-programmed outcomes rather than emergent behaviour. Besides, robotic devices in this class should be deployed in specific densities, where each robotic device has a well-defined schedule of tasks to accomplish [30,31]. These properties are also unrealistic for envisioned generic SIOs.

Hybrid robotic devices possess a combination of the features of forces-driven and mechanically inspired robotic devices. Typical hybrid robotic devices are inferred in [32] where, both, virtual forces and geometric rules are put together to trigger robotic device navigation. In their case, displacement equations are used when the robotic devices' sensory abilities detect obstacles. However, integration of different robotic device skills does not take away the complexities associated with the use of each model separately. Rather, more special cases are added to the robotic devices' motion schemes [32]. Specificities of that nature are also unattractive to the design of the envisioned generic SIOs.

Elitist robotic devices

Elitist robotic devices give rise to the third type of non-interactive robotic devices. They are designed with sufficient memories to recall previous experiences, and then use the recalled information to infer appropriate future actions. Two groups of elitist robotic devices are noted and differentiated by considering the kind of information robotic devices keep. One group can recall the entire path maps previously followed [10,33]. The other group relies on landmarks and beacons to recall the actions to take [14].

Path recalling robotic devices selectively choose the control mechanism to employ at a given time. Sometimes, they may recall the landmarks and beacons around, and use these to steer orientation [11]. In other cases, they may adopt a "memory" of what to do from the behaviour of the neighbouring counterparts [11]. However, when isolated, the same robotic devices may even make use of the direction and angle of the sun to guide their orientation [34]. A similar elitist model has been verified in [35], where robotic devices successfully used the behaviours of the neighbours to navigate with neither internal state access nor sharing of any experiences. A key parameter of emergence in these robotic devices is the mechanism in which path records are kept. Commonly, sequence generation techniques [33], and search strategies [36] are employed.

There are models whose robotic devices recall other robotic devices' identities [37], thereby steering one-on-one cooperation. As such, robotic device activities at individual levels, and the degree of success at swarm levels, are dependent on the quality of the information shared [38,39]. However, building blocks that require the use of large memory capacities are not popularly recommended in the creation of globally useful SIOs.

Landmarks and beacons-driven robotic devices also require unlimited memory to keep the properties of the landmarks and beacons [14]. Although the recalled landmarks provide direction vectors and orientation information that steer movements towards the desired directions, and though these landmarks are used to estimate Euclidean distances between the robotic devices and their targets [13], the implicit computational demands are undesirable. Desert ants have been simulated to exhibit such characteristics [40], achieving emergent behaviour without neither direct nor indirect interactions. Nonetheless, stigmergic interactions were shown to be completely impossible because the levels of the pheromone used dissipated well before they were useful to other robotic devices due to the harsh conditions in the desert. In other cases, robotic devices possess selective abilities to decide how to orientate based on the location of landmarks. Isolated robotic devices may realign by using sensory hints [41-43]. Once they are back in formation, they can follow specific vectors triggered by the information held in landmarks or other robotic devices [44]. Thus, the knowledge held by elitist robotic devices is frequently updated until deterministic emergent behaviour arises [45]. However, elitism eliminates robotic device autonomy.

INTERACTIVE MODELS

Interactive robotic devices are predominantly nature inspired. Most of them are modelled on the behaviours of living organisms such as cells [46], birds [19], DNA [47], bees [19], or ants [48]. Robotic devices in this branch depend on one another to complete individual-level tasks. Interactions, whether direct or indirect, are local. Two classes of interactive robotic devices are noted, namely, those in which interactions are one-on-one (direct), and those in which interactions are indirectly mediated *via* the environment.

Robotic devices in which interactions are one-on-one

Robotic devices in this cluster are commonly modelled with the ability to exchange information one-on-one. The information shared is often in the form of memory blocks that hold directional data [49], path histories [49], or positions of objects in the environment [12]. In some cases, robotic devices share explicit calls made in a specific robotic device communication language [50-52].

Important considerations in all robotic devices in this class pertain to the requirement to know what information should be transmitted between robotic devices, how the information is transmitted, and when it is appropriate for such information to be transmitted [53,54]. Consequently, three types of robotic devices in this group are distinguished from one another.

The first group of these robotic devices can explicitly share path histories. In these, message blocks that hold path histories in the form of stacks are hopped from one robotic device to another [55]. These stacks usually record the coordinates of the paths previously followed by robotic devices [49] or information relating to the best tours made thus far [56]. Other tuples that are shared record the entire environmental maps, including pointers to promising locations in the environment [12]. Usually, a learning framework arises [57] in which robotic devices learn the experiences of other robotic devices by explicitly referencing their stacks. Learning robotic devices can create their own roadmaps to pursue based on the experiences of their neighbours [58].

Although the notion of information sharing is nature-inspired [59], three disadvantages emanate in this category of robotic devices. First, these robotic devices should possess large memory capacities to hold the shared message blocks.

Also, these robotic devices' memory structures must be compatible with the message blocks shared. Thus, all robotic devices should be structurally similar [60]. More so, important information held in the memories of less successful robotic devices may be lost when the path histories of relatively successful robotic devices are preferred and inherited. That alone expediates information loss at swarm level.

Robotic devices that can share geometric vectors are more promising. These robotic devices do not require relatively excessive memory capacities since they would only keep a record of specific vector components [49]. There are cases where the vectors shared interpreted the levels of pheromone on the environment [61]. In other cases, these vectors interpreted the geometries of specific objects in the environment [49]. Although the features purported in these robotic devices may be considered in the design of generic SIOs, the need for substantial memory capacities is perturbing.

Robotic devices in which some form of a communication language is used have been reported as well. Most robotic device communication languages are developed with full syntax, vocabulary, and semantics only understood by those robotic devices [50]. Popular in this category are robotic device communication languages based on the growing point and origami shape theories [51]. In particular, the work of [62] is more inspiring, where a growing point language has been used to implicitly enhance pheromone dissipation in ant-like robotic devices. In other communication languages, high-level descriptions of functions and relationships among robotic devices are required upfront [63]. Such communication languages incorporate processes and properties to coordinate the behaviour of individual robotic devices for the duration of their functionality [64]. In most cases, sets of pre-programmed coordination laws and primitive behaviours are incorporated in the system upfront [65], together with the vocabulary for robotic devices to use [66]. Other robotic device languages support call protocols explicitly developed into robotic device verbs such as move, respond, avoid, recruit, or hello [67]. However, these calls are often broadcast to the entire swarm, compromising privacy and autonomy in the robotic devices.

A robotic device communication language based on geometric primitives and homeostasis maintenance has also been successfully used as an amorphous medium language [68,69]. In these works, the language was used to describe robotic device behaviour in terms of the spatial regions of the amorphous media [52], where neighbours only communicated utilizing a shared memory region [70].

Investigations aimed at identifying the primitive behaviours of ant-like robotic devices with abilities to communicate using specific communication languages have also been concluded. However, the proposed language is currently very limited in vocabulary [50]. As such, only a limited domain of emergent behaviour can be achieved. Attempts to propose robotic devices that can use sentence messages in progress [71]. However, the results presented so far lack in that the roles of receiver robotic devices are made consequences of the desires of sender robotic devices [72]. In other words, the independence of the receiver robotic devices is grossly compromised. Nonetheless, these debates are bringing us closer to the identification of explicit building blocks for the design of desired generic SIOs.

Robotic devices in which interactions are indirectly mediated

Swarm control models where robotic device interactions are indirectly mediated are predominantly adopted from chemical or biological operations. Virtual chemicals are usually placed in the environment, creating shared memories for the robotic devices in the swarms. These virtual chemicals are, often, placed into the environment in two ways, either by the objects within the environment [73], or by the robotic devices themselves [74,75]. We refer to the robotic devices in the former group as optimized, and those in the latter set as stigmergic.

Optimized robotic devices support chemical markers placed into the environment by the objects within that environment [73]. For example, chemical plume gradients have been created at specific points in the environment, which guided robotic devices to those plume sources [45,73]. What stands out in optimized robotic devices is the requirement to self-localize relative to the chemical sources [76,77]. In other words, local coordinate systems arise in which robotic devices can determine the direction to follow relative to the quality and position of particular chemicals around them [78].

In most cases, the chemicals define unidirectional paths [44]. As a result, elitist mechanisms would be required in situations where bi-directional paths are needed [7,34]. A common form of elitism involves robotic devices that can conveniently switch between different interaction strategies when it becomes necessary [12]. At times, robotic devices may use sensory cues together with chemical gradients [14]. In other cases, they may use some form of limited vision to augment chemical tracing [79]. However, the bulk of optimized robotic devices supplement chemical tracing with extra memories to recall previous experiences [80,81]. Further studies towards the identification of the primitive behaviours of optimized robotic devices are outside the scope of this review because elitism is not recommended in the design of generic SIOs [82,]. Basically, elitism takes away robotic devices' autonomy [18].

Stigmergic robotic devices, on the contrary, can excrete specific levels of pheromones [74-76]. These robotic devices make use of a non-symbolic form of communication mediated through the environment [82,83]. The term stigmergy was first used in 1959 by Grassé [84-86]. It is formed from the Greek words stigma, which means signs, and ergon which means actions. The term thus captures the notion that robotic devices' activities would leave signs in the environment, signs which determine robotic devices' subsequent actions [87].

We distinguish between two types of stigmergic robotic devices [88,89]. One group comprises sematectonic stigmergic robotic devices [87] with abilities to change the physical characteristics of the environment. Some examples of sematectonic stigmergic robotic devices were depicted in the hole making problem [36], pit construction problem [90], and nest building problem [91-95].

The second group comprises sign-based stigmergic robotic devices in which pheromone signs are dropped and marked on the environment. Although these pheromone signs may not have direct relevance to the tasks being undertaken by the robotic devices at the time, they indirectly influence subsequent robotic device actions and behaviours, including those behaviours which may be task related.

In sign-based stigmergic robotic devices, mobility is probabilistic [48]. Path selection decisions are based on the levels of pheromones held in the environment [96]. Sign-based stigmergic robotic devices are further classified into three types, namely: those that rely on a single form of pheromone, those that use two types of pheromones, and robotic devices that can use multiple levels of pheromone.

The first group of robotic devices can excrete and perceive one and only one form of pheromone. All robotic devices in this category are sensitive to that single level of pheromone regardless of the task at hand. The source of the single level of pheromone is, often, the robotic devices within the swarm itself [75]. However, there are cases where search targets have been designed with abilities to excrete this single level of pheromone [41]. However, in such cases, undesired elitism arises [97].

Among the most popular examples of single-pheromone models is the double bridge scenario [74]. In this experiment, ant-like robotic devices excrete one level of pheromone regardless of the direction in which they are traveling across the bridge. Food sources and the nest are situated on different ends of the two-way bridge. The task of each ant-like robotic device is to travel across the bridge in search of food, and upon finding the food source, pick up the resource, and return to the starting point [33,74,98]. These trips are repeated for the duration of the simulation. Trodden paths emerge along the shorter bridge, penalizing longer routes.

In most cases, single pheromone trails are unidirectional. Gradients emerge in which robotic devices move from low to high chemical concentration. However, again, elitist strategies are required when bi-directional robotic device movements are sought [34]. That requirement for elitism deems these robotic devices unsuitable for most practical applications.

Scenarios where robotic devices rely on two forms of pheromone minimize the need for elitism. Related robotic devices are prevalently sensitive to two different levels of pheromones that can co-exist in the same environment [99]. Commonly, both levels of pheromone are placed in the environment by the robotic devices, where one level is excreted when robotic devices travel from the starting point in search of the food resources, and another level is dropped when robotic devices travel in return trips [48]. However, there are cases where one or both levels of pheromones originated from other objects within the environment [100-102]. We envision SIOs that appreciate setups in which both pheromones originate from the robotic devices for potential generalizability of the SIO thereof.

Robotic devices that support multiple levels of pheromone are also available. They are designed to remedy most flaws noted in optimized, single pheromone, and two pheromone robotic devices. These robotic devices are usually built on the notion that every extra level of pheromone added would reduce elitism. As a result, the swarm intelligence systems thereof are relatively robust, fault-tolerant, flexible, and adaptive in supporting robotic device autonomy [41].

Several examples of multiple pheromone robotic devices have been simulated in medical scenarios. The work of [41] is atypical example in which mobile cancer cells are simulated as operating in human blood vessel-like environments. In their model, cancer cells can excrete the first form of pheromone called cancer pheromone, which is attractive to cancer attacking robotic devices. Cancer-free cells excrete the second level of pheromone called obstacle pheromone, which is repulsive to cancer attacking robotic devices. This mechanism ensures that cancer-attacking robotic devices do not waste time examining cancer-free cells. Upon detecting a cancer cell, a robotic device excretes the third level of pheromone called alarm pheromone, which is attractive to cancer attacking robotic devices that are still in the seeking mode. As a result, helper robotic devices can be recruited around the cancer cell to destroy the tumor. This model has inspired the development of other nanite-like robotic device deployed in similar inside-the-body environments [42,43].

Closely related to the cancer treatment model [41], was the wound detection system [97]. In this model, platelet-like robotic devices were simulated as moving inside vessel-like environments. These platelet-like robotic devices had the task to identify wounds inside blood vessels. The wounds excreted a wound pheromone which was attractive to the platelet-like robotic devices. The platelet-like robotic devices would only stick around a location if the concentration of wound pheromone was high enough to connote the presence of a wound. Robotic devices around a wound could excrete the alarm pheromone to attract other platelet-like robotic devices. Clean surfaces in the vessels were obstacle-like and excreted some repulsive levels of pheromone to platelet-like robotic devices. This way, platelet-like robotic devices' medical testing time is not wasted on clean surfaces.

A major setback for most multiple pheromone models is that the sources of these levels of pheromones are often other objects in the environment, not the robotic devices themselves, defining elitism. Robotic devices should thus be able to selectively perceive these different levels of pheromone [103,104], distinguishing between the different meanings of each level [104-106].

Some stigmergic robotic devices combined the advantages of two pheromone interaction systems with those of multiple pheromone systems [1]. The study investigated robotic device activities in scenarios where one level of pheromone was excreted when robotic devices travelled in search of the targets, and another level was excreted when robotic devices foraged back to the nest-like starting point. Related environments supported chemical markers which indicate the positions of the key objects and targets, as well as directional pheromone levels. The key advantages of robotic devices in this category are the naivety of the robotic device and complete freedom from the need to have large memory capacities. Key information is held in the environment. As a result, errors at robotic device levels do not affect the completion of tasks at swarm levels, connoting relatively robust and fault-tolerant solutions. Also, elitism is reduced or eliminated. These are attractive considerations for building generic SIOs.

DISCUSSION AND CONCLUSION

This review mainly distinguished between interactive and non-interactive robotic devices. Robotic device designs Strategies that are commonly connoted in the literature were discussed. In discussing each category, we emphasized the important characteristics of different robotic devices, splitting each category based on the interaction techniques supported (direct or indirect). Different classes of robotic devices (path recalling, geometric, language-based, optimized, stigmergic, calculus-based, forces driven, mechanical, hybrid, or beacon and landmarks based) were distinguished, highlighting commonly inferred communication strategies (direct message passing, environment mediated, sensor-based, vision, or hybrid mechanisms).

More so, this review also discussed the type of data that is commonly shared in each class of robotic devices (stacks, vectors, chemicals, forces, landmarks, or beacons). Robotic device orientation strategies were summarized along these same lines (vector-based, language-based, probabilistic, calculated directions, forces based, or cues steered by landmarks). Furthermore, we summarized the key robotic device activities at individual levels (reading stacks, interpreting language verbs, detecting chemicals, self-localizing, motion planning, or calculating directions), and indicated the key parameters of emergence that characterize each class of robotic devices (robotic device memory, verbs, elitism, robotic device abilities, environment, laws of motion, or communication mechanisms). We make the following four observations that may inspire the creation of generic SIOs:

Generally, robotic devices interaction systems emphasize orientation and movement as the key ingredients for machieving swarm intelligence. Orientation is guided by some form of meta-information such as robotic devices' sensory skills or robotic device memories. On the other hand, movement is commonly based on specific displacement factors such as attraction or repulsion effects. This observation inspires possible computational choices when system developers select primitive behaviours with which robotic devices can achieve orientation and movements. Robotic device orientation and movement are apparent policies to consider in the development of ageneric SIO.

Successful robotic device orientation relies on the availability of locally perceived information around the robotic devices (mathematical equations, geometry, forces, sensory factors, chemicals, or other robotic devices). This information is updated regularly to appropriately guide the swarm. The choices system developers may make regarding information update rules such as dropping levels of pheromones, pheromone evaporation or diffusion, vector modulation policies such as message passing, detecting targets, and normalizing vectors, can be inspired by this observation leading to the building blocks for creating generic SIOs.

We learn about the need to design robotic devices that possess some basic memory for the storage of important information. This observation inspires the architectural design of robotic device memories and the internal states thereto. In generic SIOs, robotic device state considerations and memory capacity are apparent.

Although robotic devices remain autonomous, interactive systems often create a learning framework-both at individual and communal levels-in which robotic devices collectively engineer solutions from the shared information. Related interactive robotic devices are fascinating, not because they are intelligent as individuals, but because they collectively achieve compelling emergent behaviours as swarms. The choice to investigate the actions of robotic devices can be inspired by the cooperative nature of interactive robotic devices. We are also inspired by the learning framework thereof, the dominance of interactive systems in achieving stable solutions, as well as the simplicity and naivety of related robotic devices regarding the memory needs. Generic SIOs should consider all these factors.

The value of this review is further emphasized by the following two contributions:

Categorization of robotic devices will form the basis of the generic SIO. The generic SIO will likely capture the knowledge of all these different classes of robotic devices. We believe that the SIO may better inform swarm intelligence systems developers in creating practical swarm intelligence models with a wider scope.

The parameters of emergence connoted in each case are also important components of the likely generic SIO. They may potentially inspire the choices to be made regarding the properties and quantifiers of emergency.

A few potential directions of future works emanate from the survey presented in this review. However, three future directions for research stand out.

The creation of the much-awaited generic SIO is overdue.

Another survey of the various approaches for quantifying successful emergence arising from robotic device interactions also apparent. Those pros and cons for using each specific measure of emergence in different situations can be additional meta-information in the creation of generic SIOs.

Practical applications in which deterministic emergent behaviours are evaluated using the envisioned generic SIO are also overdue. In these, specificity of the outcomes would be key.

ACKNOWLEDGMENTS

We acknowledge both the moral and technical support given by colleagues at the Sol Plaatje University, department of Computer Science, Data Science, and Information Technology. This research was also partly funded through an ABSA research grant and the CAIR (Centre for Artificial Intelligence Research) fund, 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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