Foraging Inspired Algorithms: A Design Perspective

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***Abstract*—A notable weakness of the literature concerning foraging inspired algorithms is that little attempt is typically made to rigorously identify the similarities and differences between newly proposed algorithms and existing ones. This has led to a critique from a growing number of researchers that greater efforts need to be made to consolidate the literature on foraging algorithms (and that of metaheuristics more generally) by applying a more critical perspective when assessing the worth of both current and new metaheuristics. An important part of this process is the development of taxonomies which allow us to tease out the similarities and differences between new and existing algorithms.**

This paper focusses on this issue and introduces a number of taxonomies which can be used for this purpose. It also illustrates that most foraging algorithms can be encapsulated in a high level metaframework, with differing operationalisations of elements of this framework giving rise to alternative algorithms with distinct search characteristics.

I. Introduction

Computation abounds in nature. The realisation of this fact has led to the development of the field of natural computing (NC) in which inspiration is taken from natural processes in order to design powerful algorithms for diverse applications including optimisation, classification, clustering, design and model-induction. Well-known subfields of natural computing include evolutionary algorithms, neural networks, artificial immune systems to name but a few, with Fig. 1 providing an illustrative taxonomy. A comprehensive discussion of natural computing algorithms is provided in [6].

One significant grouping of NC algorithms are those inspired by the workings of social systems and social phenomena such as the flocking and schooling behavior of fish and the behaviors observed in social insects such as ants. These social systems exhibit a number of characteristics which facilitate problem-solving including, self-organisation, flexibility, robustness, and direct/indirect communication between members of the population. These social algorithms are typically population-based like their evolutionary computation counterparts, and they generally operate by allowing the population of problem-solvers to communicate their relative success in solving the problem to each other.

An important subset of social algorithms derive their design inspiration from the foraging activities of various organisms. An interesting aspect of foraging is that it takes place in a dynamic environment as food location, and quality, changes over time as a result of factors such as consumption and degradation due to environmental influences. This suggests that higher-quality food foraging strategies need to be adaptive to changing conditions and to feedback based on their degree of past success. This aspect of foraging makes it particularly interesting as a source of inspiration for the design of algorithms for dynamic environments. Many real-world problems are 'hard' precisely because they occur in a dynamic environment.

A. Foraging Algorithms

As noted by Yeakle and Dunne (2015) [41], the behaviour of all evolutionarily successful organisms is constrained by two requirements. They must pass on their genetic material and they must acquire the necessary energy (from food) to do so. Foraging behaviours play a key role in determining evolutionary success.

The challenge facing organisms when actively foraging is 'how best to search for resources (good regions) when their location is not known with certainty a priori?'. The same problem is faced when designing search algorithms.

The observation that foraging typically requires organisms to undertake a search process has in turn led to the design of several families of search algorithms which draw metaphorical inspiration from a range of real-world foraging behaviours. Most of these algorithms embed a social foraging metaphor, with information being spread between organisms during the foraging process. While social foraging was long thought to be confined to higher-level animals such as primates, it is now known that co-operative foraging behaviours exist in many species of mammals, fish, birds, insects and even simpler organisms [23].

Families of algorithms include ant colony optimisation algorithms [4], [13], [14], [15], [16], honey bee algorithms [2], [5], [19], [20], [29], [37] and bacteria foraging algorithms [26], [27], [28].

Indeed, inspiration has been drawn from the foraging activities of a large number of organisms for the purposes of algorithmic design. Other significant families of these algorithms include those inspired by the echolocation process of bats echolocation, in which pulses of acoustic energy are emitted and the resulting echo is resolved into an 'image' of the surrounding environment, with the bat algorithm being developed by [38]. Like many other foraging inspired algorithms, the bat algorithm has produced very competitive

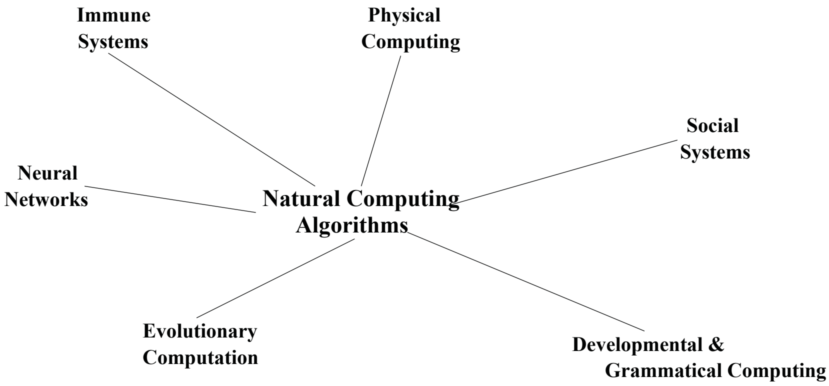

Fig. 1. An overview of some of the key groupings of natural computing algorithms

results on both benchmark optimisation problems and across a variety of applications. A detailed review of applications of the bat algorithm is provided in [40] and some extensions of the canonical algorithm are discussed in [12].

A variety of animals, including some species of birds, engage in social roosting whereby large numbers of conspecifics gather together to roost, either overnight or for longer periods. It has been claimed that these roosts can serve as *information centres* [42] to spread knowledge concerning the location of food resources in the environment. A paper by [9] draws inspiration from the social roosting and foraging behaviour of the common raven in designing the raven roosting optimisation (RRO) algorithm.

A number of studies have employed a fish school metaphor to develop algorithms for optimisation and clustering, with [1], [3], [18], [33] providing a sample of this work. Algorithms adopting this approach include fish school search (FSS) [3], the artificial fish swarm algorithm (AFSA) [22], and the fish algorithm [6]

Dominance hierarchies amongst group living animals can influence their decision-making and foraging behaviours. One example of this is provided by wolves, and a number of studies including [21], [24], [25], [36] have drawn inspiration from wolf pack foraging behaviours to design optimisation algorithms.

Obviously it is not possible to provide a detailed coverage of the entire literature on foraging inspired algorithms in a single paper. Readers requiring a comprehensive overview of this literature are referred to [10].

B. Focus of This Paper

A notable characteristic of the literature concerning foraging inspired algorithms is that little attempt is typically made to rigorously identify the similarities and differences between newly proposed algorithms and existing ones. Indeed, this critique is more broadly leveled at the entire field of metaheuristics by Kenneth Sörensen [32] amongst others, and it is accepted that a more critical perspective is required when assessing the worth of new and existing metaheuristics.

An important tool in sharpening our understanding of existing and proposed algorithms is the development of taxonomies which allow us to tease out the similarities and differences between them. In this paper we contribute to this work by introducing a number of taxonomies (Sect. II) which can be used for this purpose. We also illustrate that most foraging algorithms can be encapsulated in a high level metaframework (Sect. III), with differing operationalisations of elements of this framework giving rise to alternative algorithms with distinct search characteristics. Finally, some conclusions are discussed in Sect. IV.

II. Taxonomies of Foraging Algorithms

Given the large number of foraging inspired algorithms which have been proposed, it is not an easy task to create a taxonomy which encompasses all of them satisfactorily. In the subsections below we present a number of taxonomies which can be used to segment the population of extant algorithms. By definition, each focuses attention on one facet of the algorithms and therefore each taxonomy will have its own strengths and weaknesses.

A. Tree of Life

In Fig. 2, we divide the algorithms into three main classes, initially distinguishing between those inspired by the foraging activities of vertebrates and those arising from the foraging activities of invertebrates. In both of these classes the organisms possess a central nervous system. The third class of algorithms correspond to those inspired by the foraging activities of non neuronal organisms, in other words, organisms without a central nervous system or brain. In each of the three classes, we further subdivide the algorithms, based on their domain or kingdom.

Classifying the algorithms using this taxonomy provides a high level perspective and helps illustrate the wide variety of life forms whose foraging activities have inspired computational algorithms. It also helps highlight some gaps, such as life forms whose foraging activities have not yet been explored as a possible source of inspiration for algorithmic design.

Perhaps the most curious grouping identified is that of non neuronal life. In fact, the foraging activities of most life on earth are not driven by neuronal based decision processes. The vast majority of life forms, including the plant, bacteria, fungi and protist kingdoms of life, do not have a brain or other nervous system hardware.

Despite the absence of neuronal tissue, these apparently simple organisms live in environments that are no less complex than those faced by organisms with a brain. Traditionally, it was assumed that only higher-order animals were capable of complex decision making. However, non neuronal organisms face the same basic challenges as animals in foraging for resources, and dealing with competitors, predators and pathogens. This raises the question as to what mechanisms these organisms use for sensing their local environment, internal state, and subsequently taking adaptive actions that enhance their survival. Study of the foraging activities of these organisms, and of their decision-making processes such as quorum-based decision making, may uncover interesting, novel, approaches for algorithmic design.

The drawback of a taxonomy based on the tree of life is that it does not highlight the possible commonalities and overlaps between algorithms, as it does not provide granular detail on the search mechanisms embedded in each algorithm. This makes it difficult to critique new algorithms in terms of their degree of similarity or differentiation from existing algorithms. Below, we outline a number of alternative taxonomies which consider these mechanisms.

B. Solitary and Social Foraging

Foraging algorithms can be divided between those where each agent in the population forages alone with no social interaction with other individuals, and algorithms where there is some communication between the agents (social foraging). The vast majority of algorithms developed to date are based on a social foraging metaphor.

C. Foraging Capabilities

Foraging capabilities can be considered across several dimensions, including:

i. the sensory mechanisms available to organisms;
ii. the learning / memory capabilities available to organisms; and
iii. the communication mechanisms available to organisms.

These dimensions can be used in isolation or in conjunction with each other to create a variety of taxonomies for distinguishing between algorithms.

1) Sensory Mechanism: Taking one of these dimensions, in Table I we provide an illustration, using three families of foraging algorithms, of a taxonomy based on the primary sensory modality from which metaphorical inspiration is drawn for that algorithm: chemical sensing in the case of ant colony algorithms and bacteria foraging algorithms; and visual (observation of a waggle dance) in the case of honey bee algorithms.

Although various families of foraging inspired algorithms have produced good results on real world optimisation problems, the developed algorithms are based on very simplified models of actual underlying foraging processes, typically embedding a single sensory modality, and static social learning and information integration processes. Real world foraging behaviours are usually based on multimodal sensory information and multiple strategies for use of social learning. Foraging algorithms also typically lack a clear concept of 'perception' and 'selective attention' both of which are important elements of the extraction of information from the environment by real world organisms.

It is also notable that on close examination, the ways in which sensory mechanisms are implemented in algorithms can sometimes be quite similar, despite claims that they arise from different sensory modalities.

2) Memory Mechanism: The way that memories are created and maintained during the search process vary between algorithmic families. Table II illustrates the use of memory mechanisms as a taxonomy for classifying foraging algorithms using three sample algorithms.

In general, memory of good locations found in the past may be maintained by individuals in the population based on their own personal experience or by a subset of the population, for example dominant animals, who decide where the entire population or pack will forage next. Memory can also be maintained externally in the environment itself where for example, a trail to food is marked by early foragers allowing subsequent foragers to travel directly to the food source. In some algorithmic implementations, an external memory structure is created (which may not be biologically plausible) whereby the location of good resources once found, is maintained in an external store and the contents of this store are 'visible' to subsequent foragers. The implementation of g^{best} in the particle swarm optimisation algorithm which stores the best location ever found by the population is an example of an external storage mechanism. An additional dimension of creating a memory mechanism is how many past locations should be recorded, i.e., how far back should the memory extend? Having a more comprehensive memory mechanism could potentially be useful when attempting to adapt to a moving optimum location in a dynamic environment.

3) Communication Mechanism: Another taxonomy that can be used to distinguish between algorithms is to categorise them based on their mechanism(s) for social communication of information about food finds. Four scenarios can be distinguished. An agent may:

i. take up position at the food resource and broadcast an easily localisable signal to fellow foragers;
ii. generate a chemical or visible trail between the food resource and a central location, and then induce fellow foragers to follow this trail to the food;
iii. return to a central location and provide directions to fellow foragers on how to find the food resource; or
iv. return to a central location, recruit fellow foragers, and lead them back to the food site.

The economic balance of benefits and costs of the four options vary. Broadcasting an advertisement for a food resource from its location is relatively easy, and the related signal can be optimised for maximum range and localisation. The major

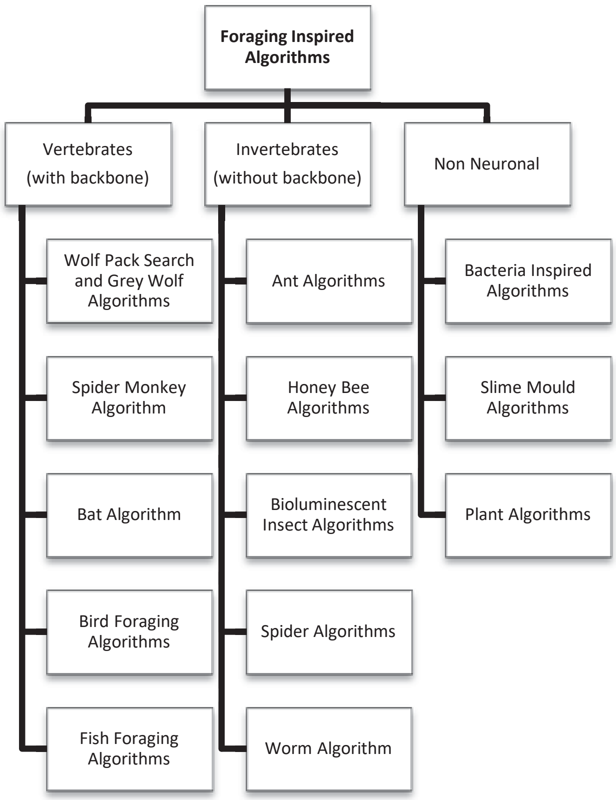

Fig. 2. Classification of foraging algorithms based on tree of life

TABLE I
MAPPING OF SENSORY MODALITIES TO ANT COLONY OPTIMISATION ALGORITHMS (ACO), BACTERIA FORAGING OPTIMISATION ALGORITHMS (BFOA), AND HONEY BEE OPTIMISATION ALGORITHMS (HBOA)

Sensory Modality	**ACO**	**BFOA**	**HBOA**
Vision	✗	✗	✔
Sound	✗	✗	✗
Chemical	✔	✔	✗
Touch	✗	✗	✗
Magnetism	✗	✗	✗
Electric	✗	✗	✗

TABLE II
MAPPING OF MEMORY MECHANISMS OF ANT COLONY OPTIMISATION ALGORITHMS (ACO), BACTERIA FORAGING OPTIMISATION ALGORITHMS (BFOA), AND HONEY BEE OPTIMISATION ALGORITHMS (HBOA)

Memory Mechanism	**ACO**	**BFOA**	**HBOA**
Personal Memory Maintained By Individual	✗	✗	✔
Populational Memory Maintained by Dominant Individual	✗	✗	✗
Memory Maintained in the Environment	✔	✔	✗
Memory Maintained in External Structure in Algorithm	✗	✗	✗

cost (risk) is that of eavesdropping as both intraspecific and interspecific competitors could use the signals to locate the advertised food resource. Predators could also use the signal to find the animal advertising the food resource.

The use of chemically-mediated trails are common in species of ants, termites, and stingless bees. These trails can create large aggregations of foragers at a food find within a short period. One risk of such trails is their interception by eavesdroppers and predators. Some insects such as stingless bees reduce this risk by creating a broken (as distinct from a continuous) trail wherein pheromone is only laid down every 5-10 metres.

Perhaps the best-known example of recruitment at a central location (such as a hive) and providing directions to fellow foragers is provided by the honeybee dance [31], [35]. The private nature of this dance (it is performed within the hive) minimises the risk of eavesdropping by non-hive members. The system is costly in that it imposes a significant cognitive burden on both senders and receivers (to produce and to process the information in the dance) and the waggle dances are also an energetically expensive display.

The final mechanism of 'communication, recruitment at a central location and subsequently leading followers back to the food site', creates fewer eavesdropper risks than broadcast signals from the food site. However, a potential leader requires a mechanism for locating likely recruits, the ability to find the food again, and sufficient compensation for the extra time and energy that leading imposes on it.

In bacteria foraging optimisation algorithms, an important mechanism is the recruitment of conspecifics to good resource locations via emission of a simulated *attractant* chemical by a bacterium, akin to broadcasting a food signal (communication mechanism i). In ant colony optimisation, the communication is via a chemical trail (mechanism ii), whereas in honey bee optimisation algorithms, the emphasis is placed on provision of detailed information as to location via a simulation of the dance process (mechanism iii). Table III illustrates the use of communication mechanisms as a taxonomy for classifying foraging algorithms.

4) Stochastic Mechanisms in Foraging Algorithms: In virtually all implementations of foraging algorithms a stochastic component is incorporated. Generally, the inclusion of stochastic mechanisms is essential in order to ensure good search performance. These mechanisms can be designed to promote exploitation and/or exploration. An example of the former is embedded in the canonical bees algorithm which intensifies search around already discovered good locations by randomly selecting trial locations within a defined hypersphere around the good location. In the case of exploration, the canonical bacteria foraging optimisation algorithm provides an example where the location of stochastically selected foragers are occasionally reinitialised to a new random locations, thereby increasing the degree of exploration in the search process. The inclusion of a suitably designed stochastic mechanism can help reduce the risk of a search process stagnating prematurely. Another approach to inclusion of a stochastic mechanism is to allow the weights assigned to different elements of the foraging strategy, such as the degree of reliance on private versus public information, to be randomly selected as the algorithm runs. This ensures that simulated foragers effectively employ more than one (fixed) foraging strategy, and bears some parallel with real world foragers who typically use multiple foraging strategies, although it does not explicitly embed context dependence. A taxonomy based on the implemented stochastic mechanisms could be used to classify foraging algorithms.

Obviously many other taxonomies could be generated in order to compare and contrast differing foraging inspired algorithms. The above exemplars are not intended to be exhaustive but rather to illustrate some of the dimensions on which algorithms can be compared and contrasted.

III. Metaframework for Algorithmic Design

In spite of the multiplicity of foraging inspired algorithms in the literature, a relatively compact metaframework can be outlined which encapsulates most existing algorithms. Four sources of information which drive foraging behaviour can be identified as in Fig. 3.

Each individual is capable of capturing information about its immediate environment via its sensory capabilities, the radius of which depends on the acuity of their senses (vision, touch, smell etc.). Individuals may also have a memory of previously successful and unsuccessful food foraging locations which they can refer to in deciding where to forage next. This is likely to be particularly useful when food locations are persistent for a period of time, or where food locations regenerate cyclically. Information about food locations may be socially transmitted between animals. In addition to the previous three influences, there is also a stochastic element to animal movement when searching for new food resources, in other words a degree of randomness as to where an animal will forage next, regardless of the private and public information it has.

The four components are combined to determine where the animal will forage next, and in essence this combination forms a foraging strategy based on a *predictive model* as the animal is attempting to predict the best next location to forage at, given the information gained so far during the search process.

A. Design of Algorithms

All foraging inspired algorithms embed each of these four components to some degree and therefore the algorithms have notable high level similarities. The four components provide a useful checklist when comparing extant algorithms or attempting to design novel algorithms. Typically, a foraging strategy will combine sensory information, memory, and social information, weighting each to varying degrees, and also include an element of 'randomness'.

While most algorithms employ a fixed search strategy based on the above, most real-world organisms employ multiple strategies, deciding which to apply based on environmental context and past payoffs. This suggests that future work in

TABLE III

MAPPING OF COMMUNICATION MECHANISMS TO ANT COLONY OPTIMISATION ALGORITHMS (ACO), BACTERIA FORAGING OPTIMISATION ALGORITHMS (BFOA), AND HONEY BEE OPTIMISATION ALGORITHMS (HBOA)

Communication Mechanism	**ACO**	**BFOA**	**HBOA**
Broadcast Signal From Resource	✗	✗	✗
Generate Chemical or Visible Signal en Route to / from Resource	✔	✔	✗
Return to Central Location and Provide Information on Location	✗	✗	✔
Return to Central Location and Lead Followers to Resource	✗	✗	✗

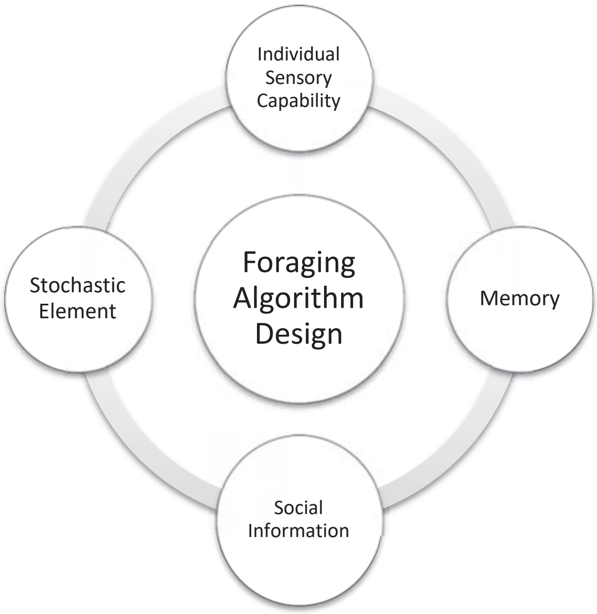

Fig. 3. Four primary components of foraging behaviour

algorithmic design could usefully include a similar multi-strategy approach.

When designing an optimisation algorithm using metaphorical inspiration from real world foraging behaviours, the modeller faces several key decisions in operationalising the metaframework.

- How do individuals sense the environment?
- What memory mechanism is implemented?
- Who transmits information in a group of foragers?
- How do they transmit information and who listens?
- How do individuals weight / combine private and social information?
- Can individuals employ multiple foraging or search strategies or do they employ a fixed strategy?

An unlimited number of specific algorithms, with differing search characteristics, can be created within this general metaframework.

IV. Discussion and Conclusions

The objective of foraging is the acquisition of valuable resources such as food, shelter and mates. A practical problem when foraging is that the location of resources in the environment is generally not known with certainty in advance. Active foraging strategies therefore, need to embed a robust search process. This observation has led to the development of a rich literature running to many thousands of papers in which several families of search and optimisation algorithms, based on the foraging strategies of various organisms, have been developed. These include ant colony algorithms, honey bee algorithms and bacteria foraging algorithms, amongst others. These algorithms have been successfully applied to many real-world problems.

Looking at foraging inspired algorithms it is evident that they are very simplified representations of real world foraging behaviours. In most algorithms the actions of a single population of agents is simulated during the search process, so important influences on foraging activities including predation risk (fear) and competition for resources, are omitted. A host of other factors which influence the choice of foraging strategy are also generally ignored in algorithmic design. Other important omissions include concepts in sensory ecology and the use of multiple foraging strategies by all but the simplest organisms. We must caution against claiming that foraging algorithms are other than very loosely inspired by foraging activities.

Of course, the fact that an algorithm omits important elements of a foraging process does not in itself invalidate its application for an optimisation, classification or other task. An algorithm is ultimately a tool for solving (or uncovering a sufficiently good solution to) a problem and its performance on that task determines whether it is considered useful. It need not necessarily be an accurate representation of the foraging process which has inspired it to be practically useful.

We have been mindful of the commentary of [32] and others, concerning the need to adopt a more critical perspective when assessing the worth of new and existing metaheuristics. In this paper we have illustrated a number of taxonomies including the categorisation of algorithms by tree of life classification, by primary (simulated) sensory modality, by memory structure, and by the mechanism they use for social communication of information. As illustrated in Sect. III, most foraging algorithms can be encapsulated in a high level framework, with differing operationalisations of elements of this framework giving rise to alternative algorithms.

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