A Taxonomy Guided Method to Identify Metaheuristic Components

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Abstract. A component-based view of metaheuristics has recently been promoted to deal with several problems in the field of metaheuristic research. These problems include inconsistent metaphor usage, non-standard terminology and a proliferation of metaheuristics that are often insignificant variations on a theme. These problems make the identification of novel metaheuristics, performance-based comparisons, and selection of metaheuristics difficult. The central problem for the component-based view is the identification of components of a metaheuristic. This paper proposes the use of taxonomies to guide the identification of metaheuristic components. We developed a general and rigorous method, TAXONOG-IMC, that takes as input an appropriate taxonomy and guides the user to identify components. The method is described in detail, an example application of the method is given, and an analysis of its usefulness is provided. The analysis shows that the method is effective and provides insights that are not possible without the proper identification of the components.

Keywords: Metaheuristic, General metaheuristic, Taxonomy.

1 Introduction

The metaheuristic research field has been criticized for inconsistent metaphor usage, non-standard terminology [1, 2], and use of poor experimental setups, validation, and comparisons [1–3]. These factors have contributed to challenges in the field such as a proliferation of novel metaheuristics and 'novel' approaches being very similar to existing approaches [1, 2, 4]. Several researchers have thus proposed that a component-based view of metaheuristics that explicitly lists metaheuristic components, will assist in identifying novel components [1, 5], promote component-based performance comparison and analyses, and facilitate component-wise selection of metaheuristics for comparative studies [1, 2, 6, 7].

A component-based view is especially important for general metaheuristics, which has enjoyed increasing popularity in recent literature. General metaheuristics, also known as general metaheuristic frameworks [8], unified metaheuristic frameworks [9], and generalized metaheuristic models [10] are used for tasks such as metaheuristic generation [10], performance analysis [11, 12], metaheuristic-similarity analysis [13], and classification of metaheuristics [7]. General metaheuristics are an abstraction of a set of metaheuristics, i.e., they are generalizations of the components, struc-

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ture, and information utilized by a set of metaheuristics [6, 12]. They thus also take a component-based view. General metaheuristics make use of a set of component-types, also referred to as general metaheuristics structures [12], component-categories [6], main ingredients [14], or key components [15].

However, general metaheuristics still suffer the challenges outlined above viz. inconsistent metaphor usage and non-standard terminology. They also suffer from similar problems if components are not properly identified. Thus, the identification of components takes on special importance.

This work promotes the systematic use of taxonomies to guide the identification of components. Our proposed method uses formal taxonomy theory, which appears to be absent in several recent metaheuristic studies that involve the creation or incorporation of taxonomies such as [7, 16–19]. Taxonomies, ideally, are built using a rigorous taxonomy building-method e.g. [20, 21]. Taxonomies are intrinsic prerequisites to understanding a given domain, differentiating between objects, and facilitating discussion on the state and direction of research in a domain [22]. Taxonomies may thus help solve the issues affecting metaheuristic research, such as non-standard terminology and nomenclature.

This work proposes the use of taxonomies to guide the identification of metaheuristic components. We developed a general and rigorous method, TAXONOG-IMC, that takes as input an appropriate taxonomy and guides the user to identify components. TAXONOG-IMC promotes the use of taxonomies to guide component identification for any metaheuristic subset, and provides guidance for the proper use of taxonomies to perform component identification.

This paper presents the method, provides an example of its application, and gives an analysis of its usefulness. The rest of the paper is structured as follows: section 2 provides a literature review, section 3 comprehensively describes TAXONOG-IMC, section 4 demonstrates the use of the method by applying it to two taxonomies to showcase its effectiveness, section 5 provides an analysis of the method by showing its effectiveness in analysing nature-inspired, population-based metaheuristics. Section 6 concludes the study.

2 Literature Review

The need for a component-based view is best appreciated in general metaheuristics. However, many general metaheuristics lack a rigorous method for identifying components. Many studies proposing a general metaheuristic provide guidance through examples of their usage. Several broad-scoped general metaheuristics follow this trend, such as general metaheuristics for population-based metaheuristics [9] and metaheuristics in general [10, 11, 13]. The general metaheuristics proposed by [6, 9, 10, 13] use mathematical formulations for their component-types. Since these mathematical formulations are sometimes in-part derived from text, the researcher can choose how to formulate a component based on their judgement and interpretation. However, this process can be negatively impacted by inconsistent metaphor usage and non-standard

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terminology. Components that are essentially the same can be regarded as different. Using examples for guidance may not account for all contingencies.

A general metaheuristic built on the assumption that differentiating the components in detail and using relatable terminology may help resolve challenges in component identification, is presented in [12]. However, most of their component-types of the general metaheuristic were a renaming of the components in [13] and may consequently face the same challenges. Some component-categories in literature were listed, but using them for the general metaheuristic may be difficult; if they consist of combinations of components, then they themselves need to be decomposed, which requires expert knowledge.

Several studies used taxonomies and/or classification-schemes to support the design of general metaheuristics. The advantage of using a taxonomy for this purpose is that it declares a convention by which the components will be identified. It provides a list of possible components that a component-type encompasses. If an issue is taken with the convention, then it can be argued at the taxonomy level. There are studies, such as [23, 24], that propose general metaheuristics whose components make use of a presented taxonomy, and there are studies that make use of existing taxonomies for a proposed general metaheuristic, such as [7, 15]. The studies that proposed both a general metaheuristic and a taxonomy are likely to work well, as the taxonomy is built for the general metaheuristic; however, taxonomies are not necessarily built with general metaheuristics in mind.

Works that use existing taxonomies lack guidance on how to use taxonomies effectively. Existing taxonomies and viewpoints were used in [15] to create a new taxonomy to guide the usage of a proposed general metaheuristic. The taxonomy presented used examples at the lowest level of its hierarchy to illustrate its usage. However, examples do not account for every contingency. The essence of the multi-level classification method proposed in [7] is meritorious; however, a misuse of the behaviour taxonomy presented in [5], led to a classification that is questionable in terms of the taxonomy used, i.e., tabu search is depicted as possessing the differential vector movement behaviour. Some studies consider tabu search as population-based but viewing tabu search as being single-solution based has a stronger consensus [25] and appears to be followed by [5], i.e., the behaviour taxonomy presented by [5] is not applicable to tabu search in its canonical sense.

The study in [14] presents a taxonomy for evolutionary algorithms based on their main components. The same study uses the taxonomy to facilitate the expression of evolutionary algorithms in terms of their main components, and the distinguishing between various evolutionary algorithm classes. This study is notable for its use of a vector representation for its components. Our work uses a similar representation.

3 Taxonomy Guided Identification of Metaheuristic Components: TAXONOG-IMC

This section proposes TAXONOG-IMC (see Fig. 1), a general, rigorous method that guides the identification of metaheuristic components using taxonomies.

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We use the definition of a taxonomy provided in [20] that lends itself to a flat representation of the metaheuristics or metaheuristic component-types, which facilitates tabular analysis. A taxonomy T is formally defined in [20] as:

$$T = \left\{D_i, (i = 1, \dots, n) \middle| D_i = \left\{C_{ij}, (j = 1, \dots, k_i); k_i \geq 2\right\}\right\} \quad (1)$$

where T is an arbitrary taxonomy, D_i is an arbitrary dimension of T, $k_i \geq 2$ is the number of possible characteristics for dimension D_i, C_{ij} an arbitrary characteristic for dimension D_i. Characteristics for every dimension are mutually exclusive and collectively exhaustive, i.e., each object under consideration must have one and only one C_{ij} for every D_i.This organization, using dimensions and characteristics, is likely to be relevant in all cases since they are fundamental to understanding the properties of objects in a domain; hence the definition (1) is used.

Some important terms concerning taxonomies are explained below:

1. Dimensions: A dimension represents some attribute of an object and can be thought of as a variable that has a set of possible values.
2. Characteristics: The characteristics of a given dimension are the possible values that can be assigned to a particular dimension.
3. Taxonomy dimension: A taxonomy dimension refers to a dimension that is part of the taxonomy under consideration. The method has steps where dimensions are proposed – these are not part of the taxonomy but are under consideration to be included. We refer to these as candidate dimensions that may then become part of the taxonomy.
4. Specialized dimension: A specialized dimension is a characteristic of a taxonomy that is promoted to dimension status; specialized dimensions are candidate dimensions.
5. Generalized dimension: A generalized dimension is created by partitioning characteristics of a taxonomy dimension or partitioning the combination of characteristics from multiple taxonomy dimensions. A generalized dimension is a candidate dimension.

To illustrate each term, consider the following dimensions of some metaheuristic: initializer, search operator, and selection. Characteristics of search operator may be, e.g., genetic crossover, swarm dynamic, differential mutation. A taxonomy for evolutionary algorithms in [14] has population, structured population, information sources etc., as its dimensions. Then population would be a taxonomy dimension. Using the behaviour taxonomy presented in [5], solution creation can be thought of as a generalized dimension of the combination and stigmergy dimensions. If we use solution-creation as a taxonomy dimension, then combination would be a specialized dimension.

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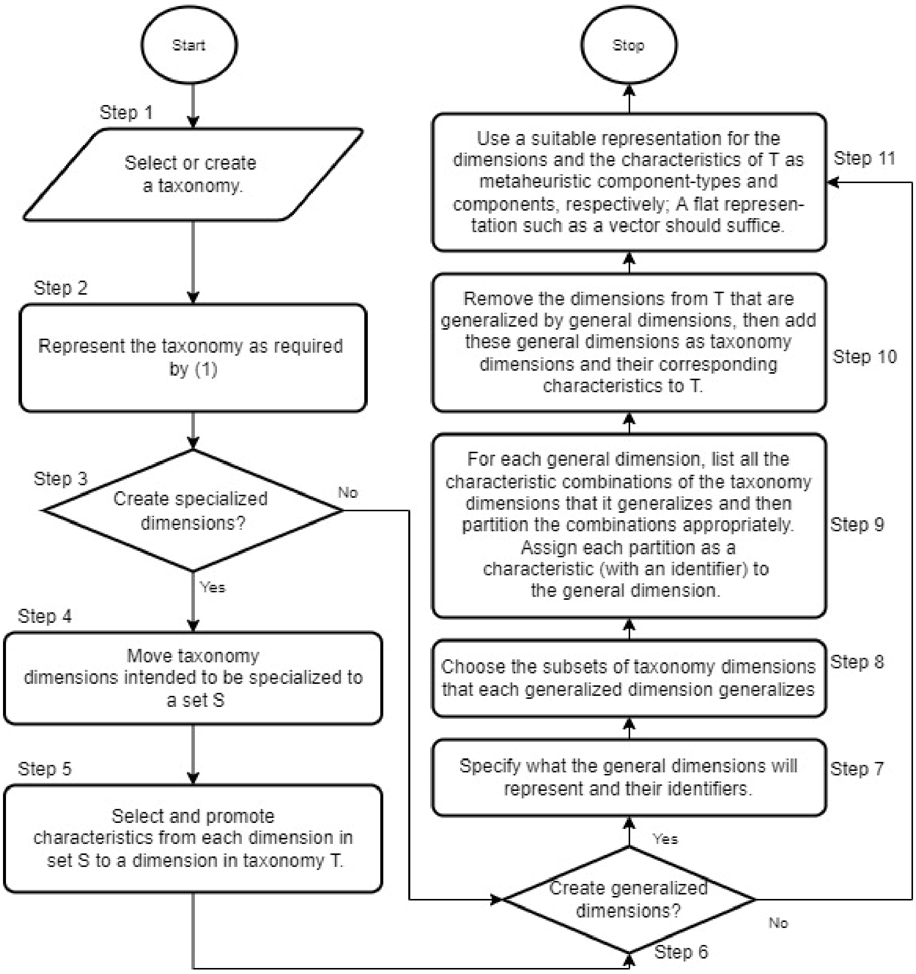

Fig. 1. Flowchart depicting the processes of TAXONOG-IMC

3.1 Comprehensive Description of Method Process

A good start for step 1 (select or create a taxonomy), is to conduct a literature search for relevant taxonomies using keywords, key-phrases, publication titles, etc. However, if no appropriate taxonomy is found, then an appropriate taxonomy building method should be used to create a taxonomy.

Expressing a taxonomy using definition (1), ensures the taxonomy is in a standard format for subsequent steps. The dimensions, and the dimensions' characteristics must be clearly stated to avoid ambiguity.

Steps 3 to 5 guides the creation of specialized dimensions. Using specialized dimensions will allow for focusing on specific components. The role of set S, introduced in step 4, is to store a collection of dimensions that are to be replaced by one of

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their characteristics in taxonomy T. In the metaheuristic context, a dimension may be replaced by more than one of its characteristics; this decision accommodates for hybrid-metaheuristics that have more than one characteristic for a dimension. When characteristics become dimensions, they will each need a set of possible characteristics of their own that will be derived from literature or the expertise of the researcher.

The addition of specialized dimensions to the Taxonomy may result in an overwhelmingly large number of taxonomy dimensions. Generalizing an appropriate number of taxonomy dimensions may help with this challenge.

Creating generalized dimensions is guided by steps 7 to 10. It is essential to name the general dimensions clearly and their characteristics to ensure no ambiguities nor confusion arises as to which dimension or characteristic a trait falls under. It is important to note that each subset of taxonomy dimensions, chosen in step 8, must be disjoint. Note that not every taxonomy dimension needs to be integrated into a general dimension.

As an example of when and how general dimensions can be used, consider a chosen set of metaheuristics that have a large diversity on certain taxonomy dimensions. They may be grouped by their characteristic combinations on these dimensions. A generalized dimension could then have two possible values, 1 representing a metaheuristic having a required combination of characteristics for those dimensions, and 0 representing a metaheuristic not having such a combination of characteristics for those dimensions.

4 Application of method

To demonstrate the method, we use it to generate binary component vectors to represent nature-inspired, population-based metaheuristics in terms of their inspiration and behaviour components. We use the behaviour and natural-inspiration taxonomies provided in [5]. In this study, we consider the metaphor/inspiration of a metaheuristic to be a component, but more specifically, a non-functional component. The nature-inspiration taxonomy was created to ascertain the natural-inspiration category of a metaheuristic without ambiguity. The behavioural taxonomy is based on the metaheuristic behaviour, i.e., focusing on the means by which new candidate solutions are obtained, and disregarding its natural inspiration. See section 4.3 for descriptions of all dimensions used by the behaviour and natural-inspiration taxonomies.

4.1 Behavior taxonomy

- Step 1: We use the behavior taxonomy from [5].
- Step 2: We express the taxonomy using the definition given in (1) as follows. A characteristic of 1 means that it is present and 0 means it is not.
  - b_1 - Combination (characteristics are {0, 1})
  - b_2 - Stigmergy (characteristics are {0; 1})
  - b_3 - All population Differential Vector Movement (DVM) (characteristics are {0; 1})

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- b_4 - Groups-based (DVM) (characteristics are {0; 1})
- b_5 - Representative based (DVM) (characteristics are {0; 1})

- Step 3: We create specialized dimensions.
- Step 4: S = {Groups-based (DVM)}, The step at this phase dictates that we only select one characteristic to promote to dimension status, but with regards to metaheuristics, which can be hybridized and still be metaheuristics, an exception can be made such that numerous characteristics can be promoted during specialization (this depends on the characteristics, if the characteristics are single-solution and population-based then these can't both be used as component-types for a metaheuristic at the same time, since there is a possibility that both can be set to 1, which does not make intuitive sense). Therefore, we promote both Sub-population (DVM) and Neighborhood (DVM) to dimensions with their characteristics being binary {0; 1}. b_4 is set to Sub-population (DVM) and b_5 is set to Neighborhood (DVM), b_6 is set to Representative based (DVM).
- Step 5: Groups-based (DVM) is not referenced by any dimension and can thus be discarded. T = {b_1; b_2; b_3; b_4; b_5; b_6 | b_i = {0; 1}; (i = 1, 2, 3, 4, 5, 6)}
- Step 6: We do not create generalized dimension.
- Step 11: The vector representation derived from the behavoiur taxonomy is:

$$[b_1 \quad b_2 \quad b_3 \quad b_4 \quad b_5 \quad b_6] \tag{2}$$

4.2 Natural-inspiration taxonomy

- Step 1: We use the natural-inspiration taxonomy from [5].
- Step 2: We express the taxonomy using the definition given in (1) as follows:

- n_1 - Breeding-based evolution (characteristics are {0; 1})
- n_2 - Aquatic animals (characteristics are {0; 1})
- n_3 - Terrestrial animals (characteristics are {0; 1})
- n_4 - Flying animals (characteristics are {0; 1})
- n_5 - Microorganisms (characteristics are {0; 1})
- n_6 - Others (characteristics are {0; 1})
- n_7 - Physics-based (characteristics are {0; 1})
- n_8 - Chemistry-based (characteristics are {0; 1})
- n_9 - Social human behaviour algorithms (characteristics are {0; 1})
- n_{10} - Plants based (characteristics are {0; 1})
- n_{11} - Miscellaneous (characteristics are {0; 1})

- Step 3: We do not create specialized dimensions.
- Step 6: We create general dimensions.
- Step 7: We create two general dimensions that will be identified as Swarm-intelligence and Physics and Chemistry Based. (This is already done in the taxonomy, but we are redoing it in this process for demonstration).
- Step 8: Aquatic animals, Terrestrial animals, Flying animals, Microorganisms, Others are allocated to the Swarm-intelligence general dimension. Physics-based,

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Chemistry-based are allocated to the Physics and Chemistry Based general dimension.
- Step 9: The characteristics of Swarm-intelligence are {0; 1}. 1 indicating that either Aquatic animals, Terrestrial animals, Flying animals, Microorganisms, or Others are present, 0 indicating that Aquatic animals, Terrestrial animals, Flying animals, Microorganisms, and Others are absent. The characteristics of Physics and Chemistry Based are {0; 1}. 1 indicating that either Physics-based or Chemistry-based is 1, 0 indicating that Physics-based and Chemistry-based are absent.
- Step 10: Since n_2 to n_8 are removed, n_2 will be the dimension for Swarm-intelligence, n_3 will be the dimension for Physics and Chemistry Based, n_4 will be the dimension for Social human behavior algorithms, n_5 will be the dimension for Plants based, n_6 will be the dimension for Miscellaneous; n_7 to n_{11} do not refer to any dimensions so they can be discarded. T = {n_1; n_2; n_3; n_4; n_5; n_6 | n_i = {0; 1}, (i = 1, 2, 3, 4, 5, 6)}
- Step 11: The vector representation definition derived from the selected taxonomy is:

$$[n_1 \quad n_2 \quad n_3 \quad n_4 \quad n_5 \quad n_6] \tag{3}$$

4.3 Dimension Descriptions

In this sub-section, the nodes of each hierarchal taxonomy presented in [5] are unambiguously defined as dimensions using the descriptions of each node provided in the same study; from these definitions, we can define the dimensions in the initial steps and proceed to modify them in subsequent steps by adding and/or dropping these dimensions due to using generalized or specialized dimensions.

Behaviour Dimensions

- Differential vector movement: New solution is obtained by movement relative to an existing solution
- All population Differential Vector Movement (DVM): All individuals in the population are used to generate the movement of each solution.
- Representative-based (DVM): The movements of each solution are only influenced by a small group of representative solutions, e.g., the best solutions found
- Group-based (DVM): Sub-populations or subsets of the populations are considered, without representative solutions.
- Sub-population (DVM): The movements of each solution are influenced by a subset or group of solutions in the population, and no representative solutions are determined and used in the trajectory calculation at hand.
- Neighborhood (DVM): Each solution is only influenced by solutions in its local neighborhood.
- Combination: New solutions are selected and combined via some method to create new solutions.
- Stigmergy: An indirect communication and coordination strategy is used between different solutions to create new solutions.

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- Creation: Exploration of search domain by generating new solution, differential vector movement not present.

Natural-Inspiration Dimensions

- Breeding-based evolution: Inspired by the principle of natural evolution and references to producing offspring, successive generations.
- Swarm Intelligence: Inspired by the collective behavior of animal societies.
- Flying animals: Agent movements inspired by flying movements.
- Terrestrial animals: Agent movements inspired by foraging or movements of terrestrial animals.
- Aquatic animals: Agent movements inspired by animals living in aquatic ecosystems.
- Microorganisms: Agent movements inspired by food search by bacteria or how viruses spread infection.
- Others: Very low popularity inspiration sources from the collective behavior of animals.
- Physics and Chemistry Based: Imitate the behavior of physical/chemical phenomena (field of physics and chemistry).
- Social Human Behavior Algorithms: Inspired by human social concepts.
- Plants Based: Inspired by plants, where there is no communication between agents.
- Miscellaneous: Not inspired by any identified category.

5 Analysis and Discussion

We now demonstrate the use of the method. Information showing the application frequency of different nature-inspired metaheuristics to feature selection in disease diagnosis is depicted in Table 10 taken from the study in [26]. It is stated that data for the table was obtained by executing various search queries on google scholar. RA is not population-based, and thus is ignored since it is out of scope for the vector derived in the current paper. In this section, the amount of information extracted from Table 10 in [26] is extended using the derived vector. The aim is to reconfigure the table to attribute the frequencies to the component-types of the derived vector. This task is accomplished via the following steps:

1. List all metaheuristic abbreviations and ascertain their full name.
2. Represent each of the nature-inspired, population-based metaheuristics using the vector formats derived, i.e., (2) and (3), as shown in Table 1. If the metaheuristics were not present in the tables, the descriptions of the dimensions of the taxonomies presented in [5] would have to be used to derive their vector representation.
3. Let B be a matrix representing the data of Table 1, i.e., $B[p][q]$ will indicate whether the component-type at column index q is present in the metaheuristic at row index p. Let D be a matrix where each intersection of row i and column j is the frequency of application of metaheuristic at row index i to the disease at column index j (D holds the data of Table 10 in [26]). Let F be the matrix that holds

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the component-type to disease diagnosis application frequencies (Table 2), i.e., where j is index number of the disease in the columns of Table 10 presented in [26] and q is the index number of the component-type in the vector:

$$F[j][q] = \sum_{x=0}^{N} B[x][q] \times D[x][j] \tag{4}$$

4. Matrix F contains the data of Table 2 that depicts the table of frequency of appl cation of a component-type to disease diagnosis. From this table, further analysis can be done.

Table 1. Representation of nature-inspired, population-based metaheuristics in terms of derived vector formats.

KEY: Harmony search (HS), Artificial bee colony (ABC), Glow-worm swarm optimization (GSO), Ant colony optimization (ACO), Firefly algorithm (FA), Monkey algorithm (MA), Cuckoo search (CS), Bat algorithm (BA), Dolphin echolocation (DE), Flower pollination algorithm (FPA), Grey wolf optimizer (GWO), Dragonfly algorithm (DA), Krill herd algorithm (KHA), Elephant search algorithm (ESA), Ant lion optimizer (ALO), Moth-flame optimization (MFO), Multi-verse optimizer (MVO), Runner-root algorithm (RRA), Laying chicken algorithm (LCA), Killer whale algorithm (KWA), Butterfly optimization algorithm (BOA).

PMBH	**b1**	**b2**	**b3**	**b4**	**b5**	**b6**	**n1**	**n2**	**n3**	**n4**	**n5**	**n6**
HS	1	0	0	0	0	0	0	0	1	0	0	0
ABC	0	0	0	0	0	1	0	1	0	0	0	0
GSO	0	0	0	0	0	1	0	1	0	0	0	0
ACO	0	1	0	0	0	0	0	1	0	0	0	0
FA	0	0	1	0	0	0	0	1	0	0	0	0
MA	0	0	0	0	0	1	0	1	0	0	0	0
CS	1	0	0	0	0	0	0	1	0	0	0	0
BA	0	0	0	0	0	1	0	1	0	0	0	0
DE	1	0	0	0	0	0	0	1	0	0	0	0
FPA	0	0	0	0	0	1	0	0	0	0	1	0
GWO	0	0	0	0	0	1	0	1	0	0	0	0
DA	0	0	0	0	0	1	0	1	0	0	0	0
KHA	0	0	0	0	0	1	0	1	0	0	0	0
ESA	0	0	0	0	0	1	0	1	0	0	0	0
ALO	0	0	0	0	0	1	0	1	0	0	0	0
MFO	0	0	0	0	0	1	0	1	0	0	0	0
MVO	0	0	0	0	0	1	0	0	1	0	0	0
RRA	0	0	0	0	0	1	0	0	0	0	1	0
LCA	1	0	0	0	0	0	0	1	0	0	0	0
KWA	0	0	0	0	0	1	0	1	0	0	0	0
BOA	0	0	0	0	0	1	0	1	0	0	0	0

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Table 2. Frequencies of component-type usage, in literature, in various disease diagnosis applications

Disease diagnosis	b_1	b_2	b_3	b_4	b_5	b_6	n_1	n_2	n_3	n_4	n_5	n_6
Breast cancer	413	619	216	0	0	893	0	1859	236	0	46	0
Prostate cancer	35	73	9	0	0	68	0	161	21	0	3	0
Lung cancer	105	157	41	0	0	154	0	400	51	0	6	0
Oral cancer	4	3	2	0	0	6	0	12	3	0	0	0
Neck cancer	4	4	0	0	0	9	0	13	3	0	1	0
Skin cancer	19	4	15	0	0	53	0	81	8	0	2	0
HIV	40	114	24	0	0	80	0	237	18	0	3	0
Stroke	116	120	36	0	0	129	0	330	60	0	11	0
Schizophrenia	8	44	9	0	0	16	0	72	4	0	1	0
Parkinson	91	144	52	0	0	233	0	434	62	0	24	0
Heart disease	129	34	58	0	0	234	0	390	55	0	10	0
Anxiety	17	65	9	0	0	50	0	135	5	0	1	0
Insomnia	1	6	0	0	0	2	0	9	0	0	0	0
Sum	982	1387	471	0	0	1927	0	4133	526	0	108	0

It can be observed from Table 2 that b_6 (Representative-based (DVM)) is the dominant behaviour and n_2 (Swarm intelligence) is the dominant natural-inspiration. It is interesting to note that in [26], it is stated that ACO is dominant in the use of diagnosis of different human disorders. However, the behaviour associated with ACO is Stigmergy (b_2) is not the dominant behaviour; instead, representative-based differential movement (b_6) is the dominant behaviour for this application domain.

Literature such as [1] has shown that the names and metaphors of metaheuristics sometimes mask the substantial similarities between the metaheuristics and their differences are so minute that they can be considered marginal variants. ACO is popular, but the problem could lie with many metaheuristics, which have behavioural component-type b_6, being diverse in names as this trend is either diluting the core algorithm's popularity or is misguiding users to believe that different metaheuristic names entail that they have nearly orthogonal behaviours.

From Table 2, it can be ascertained that scope for future research lies in applying metaheuristics with behavioural component-types: sub-population (DVM), neighbourhood (DVM), breeding-based evolution, social-human behaviour algorithms, and miscellaneous to disease diagnosis. Even though the three latter component-types are natural-inspirations, and literature has motivated that this category of component-types has little contribution to performance. Applying them increases their presence in a population, from which data can be sampled, i.e., a diverse population is good.

The taxonomies in [5] organized the metaheuristics using their canonical versions. This study relies on the assumption that if two or more metaheuristic-algorithms are associated with the same metaheuristic, then they should possess the behaviour of that metaheuristic. The proposed method can be used to select components for metaheuristic frameworks, classification schemes, representations, and comparative analysis.

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6 Conclusion

This study proposes TAXONOG-IMC, a structured method that provides guidance for metaheuristic component identification using taxonomies. An example application is provided to showcase how TAXONOG-IMC can aid in metaheuristic analysis.

Identification of metaheuristic components is an important task for the effective use of general metaheuristics, and the metaheuristic component-based view by and large. General metaheuristic publications use strategies such as providing examples, using finer-grain component-types, relying on existing taxonomies or creating new ones to assist in component identification. However, examples don't account for all contingencies that a researcher may encounter, and finer-grain components can also be affected by non-standard terminology and inconsistent metaphor usage. There are general metaheuristic publications that use taxonomies to assist in component identification; some propose their own taxonomy, and others use an existing taxonomy. The ones that propose their own taxonomy are likely to be compatible with the general metaheuristic since they are created for that purpose; however, some of the publications that use existing taxonomies made questionable decisions during the demonstration of general metaheuristic use – indicating a lack of proper use of taxonomy.

Future research lies in using taxonomies for component-identification for many other metaheuristic subsets, metaheuristics analysis, and use in general metaheuristics.

References

1. Sörensen, K.: Metaheuristics-the metaphor exposed. International Transactions in Operational Research. 22, 3–18 (2015). https://doi.org/10.1111/itor.12001.
2. Aranha, C., Camacho Villalón, C.L., Campelo, F., Dorigo, M., Ruiz, R., Sevaux, M., Sörensen, K., Stützle, T.: Metaphor-based metaheuristics, a call for action: the elephant in the room. Swarm Intelligence. (2021). https://doi.org/10.1007/s11721-021-00202-9.
3. García-Martínez, C., Gutiérrez, P.D., Molina, D., Lozano, M., Herrera, F.: Since CEC 2005 competition on real-parameter optimisation: a decade of research, progress and comparative analysis's weakness. Soft Comput. 21, 5573–5583 (2017). https://doi.org/10.1007/s00500-016-2471-9.
4. Tzanetos, A., Dounias, G.: Nature inspired optimization algorithms or simply variations of metaheuristics? Artificial Intelligence Review. 54, 1841–1862 (2021). https://doi.org/10.1007/s10462-020-09893-8.
5. Molina, D., Poyatos, J., Ser, J.D., García, S., Hussain, A., Herrera, F.: Comprehensive Taxonomies of Nature- and Bio-inspired Optimization: Inspiration Versus Algorithmic Behavior, Critical Analysis Recommendations. Cognitive Computation. 12, 897–939 (2020). https://doi.org/10.1007/s12559-020-09730-8.
6. Peres, F., Castelli, M.: Combinatorial Optimization Problems and Metaheuristics: Review, Challenges, Design, and Development. Applied Sciences. 11, 6449 (2021). https://doi.org/10.3390/app11146449.

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7. Stegherr, H., Heider, M., Hähner, J.: Classifying Metaheuristics: Towards a unified multi-level classification system. Natural Computing. (2020). https://doi.org/10.1007/s11047-020-09824-0.
8. Birattari, M., Paquete, L., Stützle, T.: Classification of Metaheuristics and Design of Experiments for the Analysis of Components. (2003).
9. Liu, B., Wang, L., Liu, Y., Wang, S.: A unified framework for population-based metaheuristics. Annals of Operations Research. 186, 231–262 (2011). https://doi.org/10.1007/s10479-011-0894-3.
10. Cruz-Duarte, J.M., Ortiz-Bayliss, J.C., Amaya, I., Shi, Y., Terashima-Marín, H., Pillay, N.: Towards a Generalised Metaheuristic Model for Continuous Optimisation Problems. Mathematics. 8, 2046 (2020). https://doi.org/10.3390/math8112046.
11. De Araujo Pessoa, L.F., Wagner, C., Hellingrath, B., Buarque De Lima Neto, F.: Component Analysis Based Approach to Support the Design of Meta-Heuristics for MLCLSP Providing Guidelines. In: 2015 IEEE Symposium Series on Computational Intelligence. pp. 1029–1038. IEEE, Cape Town (2015). https://doi.org/10.1109/SSCI.2015.149.
12. Stegherr, H., Heider, M., Luley, L., Hähner, J.: Design of large-scale metaheuristic component studies. In: Proceedings of the Genetic and Evolutionary Computation Conference Companion. pp. 1217–1226. ACM, Lille France (2021). https://doi.org/10.1145/3449726.3463168.
13. de Armas, J., Lalla-Ruiz, E., Tilahun, S.L., Voß, S.: Similarity in metaheuristics: a gentle step towards a comparison methodology. Natural Computing. (2021). https://doi.org/10.1007/s11047-020-09837-9.
14. Calégari, P., Coray, G., Hertz, A., Kobler, D., Kuonen, P.: A Taxonomy of Evolutionary Algorithms in Combinatorial Optimization. Journal of Heuristics. 5, 145–158 (1999). https://doi.org/10.1023/A:1009625526657.
15. Raidl, G.R.: A Unified View on Hybrid Metaheuristics. In: Almeida, F., Blesa Aguilera, M.J., Blum, C., Moreno Vega, J.M., Pérez Pérez, M., Roli, A., and Sampels, M. (eds.) Hybrid Metaheuristics. pp. 1–12. Springer Berlin Heidelberg, Berlin, Heidelberg (2006). https://doi.org/10.1007/11890584_1.
16. Kaviarasan, R., Amuthan, A.: Survey on Analysis of Meta-Heuristic Optimization methodologies for node Network Environment. In: 2019 International Conference on Computer Communication and Informatics (ICCCI). pp. 1–4. IEEE, Coimbatore, Tamil Nadu, India (2019). https://doi.org/10.1109/ICCCI.2019.8821838.
17. Fister, I., Perc, M., Kamal, S.M., Fister, I.: A review of chaos-based firefly algorithms: Perspectives and research challenges. Applied Mathematics and Computation. 252, 155–165 (2015). https://doi.org/10.1016/j.amc.2014.12.006.
18. Diao, R., Shen, Q.: Nature inspired feature selection meta-heuristics. Artif Intell Rev. 44, 311–340 (2015). https://doi.org/10.1007/s10462-015-9428-8.
19. Donyagard Vahed, N., Ghobaei-Arani, M., Souri, A.: Multiobjective virtual machine placement mechanisms using nature-inspired metaheuristic algorithms in cloud environments: A comprehensive review. Int J Commun Syst. 32, e4068 (2019). https://doi.org/10.1002/dac.4068.
20. Nickerson, R.C., Varshney, U., Muntermann, J.: A method for taxonomy development and its application in information systems. European Journal of Information Systems. 22, 336–359 (2013). https://doi.org/10.1057/ejis.2012.26.

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DOI: 10.1007/978-3-031-08757-8_41

21. Usman, M., Britto, R., Börstler, J., Mendes, E.: Taxonomies in software engineering: A Systematic mapping study and a revised taxonomy development method. Information and Software Technology. 85, 43–59 (2017). https://doi.org/10.1016/j.infsof.2017.01.006.
22. Szopinski, D., Schoormann, T., Kundisch, D.: BECAUSE YOUR TAXONOMY IS WORTH IT: TOWARDS A FRAMEWORK FOR TAXONOMY EVALUATION. Research Papers. (2019).
23. Krasnogor, N., Smith, J.: A Tutorial for Competent Memetic Algorithms: Model, Taxonomy, and Design Issues. IEEE Transactions on Evolutionary Computation. 9, 474–488 (2005). https://doi.org/10.1109/TEVC.2005.850260.
24. Stork, J., Eiben, A.E., Bartz-Beielstein, T.: A new taxonomy of global optimization algorithms. Natural Computing. (2020). https://doi.org/10.1007/s11047-020-09820-4.
25. Glover, F., Laguna, M.: Tabu Search Background. In: Tabu Search. pp. 1–24. Springer US, Boston, MA (1997). https://doi.org/10.1007/978-1-4615-6089-0_1.
26. Sharma, M., Kaur, P.: A Comprehensive Analysis of Nature-Inspired Meta-Heuristic Techniques for Feature Selection Problem. Archives of Computational Methods in Engineering. 28, 1103–1127 (2021). https://doi.org/10.1007/s11831-020-09412-6.

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