Metaheuristic Design Pattern: Preference

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ABSTRACT
In interactive metaheuristic design, the human helps to steer the trajectory of the search by providing qualitative evaluation to assist in the selection of solution individuals. Exploiting human qualitative evaluation in search provides a mechanism for exploring trade-off judgments among competing criteria taking into account human implicit knowledge and experience. This paper proposes the Preference metaheuristic design pattern involving six abstractions across explicit and implicit knowledge and *a priori*, interactive and *a posteriori* dimensions.

Keywords – Interactive metaheuristic search, design patterns, preference.

1. PROBLEM STATEMENT
In interactive metaheuristic search, the human helps to steer the trajectory of the search by providing qualitative evaluation to assist in the selection of solution individuals [1]. Integrating the human "in-the-loop" enables metaheuristic search to be steered by either qualitative evaluation alone or combining human qualitative evaluation with quantitative objective fitness functions.

However, human evaluation relies on user preference which can be expressed in a variety of ways. User preference information can range from tacit qualitative assessments that are difficult for humans to articulate to more explicit statements of desiderata. User preference may also by multi-faceted (or "multi-subjective") in that many preference concerns are simultaneously evaluated [2, 3]. It is challenging to design metaheuristic search to effectively and efficiently incorporate user preference information, both in terms of the nature of the preference information being exploited, and the timing of its exploitation in relation to metaheuristic search.

2. THE SOLUTION
The Preference metaheuristic design pattern increases the value of preference information along two dimensions i.e., the nature of the preference information and the timing of the preference information during search.

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The nature of user preference information ranges from implicit to explicit:

- *Implicit preferences* may be tacit and difficult for humans to articulate, since implicit memory is a type of memory in which previous experiences aid the performance of a task without conscious awareness of these previous experiences [4, 5]. Even though they may not able to articulate why they have evaluated a solution individual, users can make valid solution evaluations by means of reference to a preference scale, or comparison of two solution individuals, or ranking of multiple solution individuals based on preference.
- *Explicit preferences* are readily articulated by users and their relevance to metaheuristic search is typically well understood by the user (e.g., [6]).

The timing of preference incorporation in metaheuristic search ranges from before search (*a priori*), to during search (interactive) to after search (*a posteriori*) [7, 8, 9]:

- Using an *a priori* method, preference information is provided before metaheuristic search is conducted. *A priori* preference information may be useful in addressing "multi-subjective" concerns.
- Using an interactive method, preference information is provided during the metaheuristic search. Interactive preference information may be useful in refining the fitness evaluation of solution individuals. Such interactive methods have been referred to as "human-in-the-loop" metaheuristic search.
- Using an *a posteriori* method, preference information is provided after metaheuristic search has been executed and may be useful in the user selection of solutions individuals from a set or population of optimal solutions.

Combining the two dimensions of preference information gives six potential design pattern abstractions:

- *Implicit preference, a priori:* even though users cannot easily articulate their preferences, metaheuristic search attempts to afford flexible mechanisms for their incorporation;
- *Implicit preference, interactive:* users are offered opportunities to input preference to metaheuristic search either as qualitative evaluation solely or in combination with quantitative objective fitness functions;

- *Implicit preference, a posteriori:* users are prompted for subjective preference feedback which may be exploited in adaptive learning of preference information;
- *Explicit preference, a priori:* user preference information may be exploited, for example, to convert a multi-objective optimization problem into a single objective problem by means of weight configuration (e.g., [10]);
- *Explicit preference, interactive:* preference information may be provided by the user in the form of an ideal or reference point(s) which can be exploited in multi-objective metaheuristic search to guide the trajectory to preferred regions within the search space;
- *Explicit preference, a posteriori:* preference information may be useful after metaheuristic search has been executed in the user selection of solutions individuals from a set or population of optimal solutions.

3. CONSEQUENCES

Where user preference information is explicit, *a priori* and interactive approaches can be beneficial. On the other hand, where user preference information is implicit, interactive and *a posteriori* approaches may be more appropriate. It is also possible for user preference information to be exploited at different stages of metaheuristic search. Thus the major force driving the significant trade-off in the preference pattern is to distinguish the nature of user preference information along a continuum from implicit to explicit. The more explicit the preference, the earlier in metaheuristic search the preference can be exploited for effective and efficient search.

4. EXAMPLES

Table 1 summarizes examples of the Preference pattern along the two dimensions. It is interesting to note that examples of implicit *a priori* approaches are not readily available in the literature; furthermore few examples of explicit *a posteriori* examples are available. It is also noteworthy that some examples combine a number of approaches. For example, Chica et al. [11] report the use of implicit and explicit preferences, combined with *a priori*, interactive and *a posteriori* timing. A discussion of a selection of examples of pattern application follows Table 1.

Table 1: Preference Natures and Approaches

	a priori	interactive	*a posteriori*
Implicit		Agarawal [12], Avigad [13], Babbar-Sebens [14], Branke [15], Fukumoto [16], Jaimes [17], Kim [18], Parmee [19], Sayyad [20], Simons [21].	Chica [11], Duenas [22], FukuMoto [16], Sayyad [20].
Explicit	Chankong [10], Chica [11], Duenas [22], Thiele [23], Xiong [24].	Luque, [25], Branke [15], Chica [11], Cho [26], Gong [27], Gong [28], Hettenhausen [29], Karahan [30], Koksalan [31], López-Ibánez [32], Thiele [23], Xiong [24].	Hettenhausen [33].

4.1 Applying Implicit Preference Information

Agrawal et al. [12] propose an interactive particle-swarm metaheuristic for multiobjective optimization that seeks to encapsulate Pareto dominance and interactive decision making in its solution mechanism. The user is provided with the knowledge of an approximate Pareto optimal front, and his/her preference articulations are used to derive a utility function intended to calculate the utility of the existing and upcoming solutions. The incubation of particle-swarm mechanism by incorporating an adaptive-grid mechanism, a self-adaptive mutation operator, and a novel decision-making strategy makes it an effective and efficient approach. In a different example, Avigad and Moshaiov [13] use implicit preference information in a concept-based approach. In this search, conceptual solutions are represented by sets of particular individuals, with each concept having a one-to-many relation with the objective space. Avigad and Moshaiov assert that such a set-based concept representation is suitable for human–centred interactive search.

In contrast, Babbar-Sebens and Minsker [14] recognize that interactive users are likely to go through their own learning process as they view new solutions and gain tacit knowledge about a design space. This leads to temporal changes in their preferences that might impair the performance of interactive optimization algorithms. To address this, Babbar Sebens and Minsker propose the use of case-based memory and case-based reasoning to manage the effects of changing implicit user preferences within the search process. In another example application, implicit preferences have been harnessed by Fukumoto et al. [16] in Interactive Tabu Search (ITS) for highly subjective user evaluation of blended fragrances composed of several aroma sources. The strength of each aroma source was target of optimization. However, it seemed difficult for the users to decide the best fragrance from several fragrances with sequential presentation. Their study focuses on proposing an enhanced ITS method using paired comparison based on implicit preference successively used for deciding the best individual from the population in a manner akin to tournament selection.

In a further example application, Sayyad et al. [20] investigate implicit user preference in the configuration of software product lines (expressed as feature maps) using various search-based software engineering methods. As the number of optimization objectives increases, it emerges that methods in widespread use (e.g., NSGA-II, SPEA2) perform much worse than an Indicator-

Based Evolutionary Algorithm (IBEA). IBEA appears to perform effectively because of its exploitation of user preference knowledge. A further example of integrating implicit user preferences can be found at Simons et al. [21] who use an interactive Ant Colony Optimization (iACO) approach. As a part of the iACO, users provide an evaluation of early lifecycle software designs based on a subjective preference of symmetrical elegance of the designs as an indicator of design quality. Chica et al. [11] use *a posteriori* implicit preference to tackle a realistic variant of the classical assembly line problem formulation, i.e., time and space assembly line balancing. Their goal is to study the influence of incorporating user preferences based on Nissan automotive domain knowledge to guide the multi-objective search process with two different aims; reduce the number of equally preferred assembly line configurations, and then provide the plant managers with configurations of their contextual interest in the objective space.

4.2 Applying Explicit Preference Information

Starting with examples on using *a priori* preferences, Dunneas et al. [22] apply a genetic algorithm to attempt to solve the nurse scheduling problem for nursing staff in a hospital. In this empirical study, the preferences of the Head Nurse are modelled by fuzzy sets and aggregated to determine an overall preference cost function to generate good quality solutions. In another example using *a priori* preference information, Thiele et al. [23] discuss the idea of incorporating preference information into evolutionary multiobjective optimization. Each new population is generated by the fitness function which combines user preference information in an achievement scalarizing function. In multiobjective optimization, achievement scalarizing functions are widely used to project a given reference point into the Pareto-optimal set. In the approach proposed by Thiele et al., the next generation is thus more concentrated in the region where more preferred alternatives are assumed to lie and the whole Pareto-optimal set does not have to be generated with equal accuracy. The approach is demonstrated by numerical examples.

In contrast, integrating explicit user preference interactively is also widely used. For example, Luque et al. [25] introduce new ways of utilizing preference information specified by the user in interactive reference point based methods. A reference point consists of desirable values for each objective function. Their approach incorporates the desires of the user more closely when projecting the reference point onto the set of nondominated solutions. In a further example, Cho and Lee [26] developed an image retrieval system based on human preference and emotion within an Interactive Genetic Algorithm (IGA). This system extracts features from images by wavelet transform, and the authors claim to provide a user-friendly means to retrieve an image from a large database when the user cannot clearly define what the image must be. In another investigation by Karahan and Koksalan [30], a steady-state elitist evolutionary algorithm has been developed to approximate Pareto-optimal frontiers of multiobjective decision making problems. The algorithm defines a territory around each individual to prevent crowding in any region. The user preference information was thus employed in order to focus on the regions that appeal to the preference of the user. Their experiments show that the algorithm approximates Pareto-optimal solutions in the desired region very well when incorporated with preference information. In other research, López-Ibánez and Knowles [32] control the direction of search by user preferences elicited in an interactive technique using an evolutionary multi-objective optimization algorithm. López-Ibánez and Knowles propose a conceptual framework of quantitative assessment, based on the definition of machine decision makers, made somewhat realistic by the incorporation of various non-idealities.

As mentioned before, few researchers report the use of *a posteriori* explicit user preference. However, one example can be found at Hettenhausen et al. [33], wherein an interactive Multi-Objective Particle Swarm Optimization (MOPSO) method is introduced. This method allows the user to guide the optimization process based on domain-specific knowledge and problem-specific preferences. In order to make it easier for the user to provide his/her preferences, a graphical user interface tool is provided and combined with MOPSO such that user satisfaction could be directly elicited and exploited in the algorithm.

5. REFERENCES

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