

# Signaling and Visualization for Interactive Evolutionary Search and Selection of Conceptual Solutions

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## ABSTRACT

This paper deals with the problem of selecting and ordering a pre-defined number of conceptual solutions (concepts) out of a given finite set of candidate concepts. The process involves human intervention which allows the inclusion of un-modeled considerations, as well as the saving of computational resources. To support human intervention special visualization elements are developed. The proposed interactive method is demonstrated on a path planning problem using the method of Evolution Strategies.

## Categories and Subject Descriptors

G.1.6 Optimization

## General Terms

Algorithms, Performance, Experimentation.

## Keywords

Interactive Evolutionary Computation, Set-based Concept.

## 1. INTRODUCTION

Concept generation and selection is done in an early stage of the engineering design process [1]. In that stage it is common to have a high level of uncertainty and a low level of computational models. Hence, concept selection, at that stage, is primarily a human-based process. Given the significance of concept selection on the success or failure of the design, researchers attempt to develop methods to support and rationalize the process of concept selection. Here we concentrate on a non-traditional approach to concept selection with computer support, which is known as the *Set Based Concept (SBC)* approach [2].

To better understand the problem of selection and ordering of concepts, the reader is referred to the conceptual path planning example which is illustrated in figure 1. Assume that the first

concept is defined as the set of all feasible paths that go from the start point to the goal point by passing left to obstacle 'A' (e.g., the particular paths p1 and p2). Similarly, a second concept contains the set of all feasible paths that pass between obstacles 'A' and 'B' (e.g., the particular paths p3 and p4). Finally, a third concept contains the set of all feasible paths that pass between obstacles 'B' and 'C' (e.g., the particular paths p5 and p6). One possible definition of a conceptual path planning, problem, for the described environment and concepts, could be to select and order the best two concepts out of the three candidate ones.

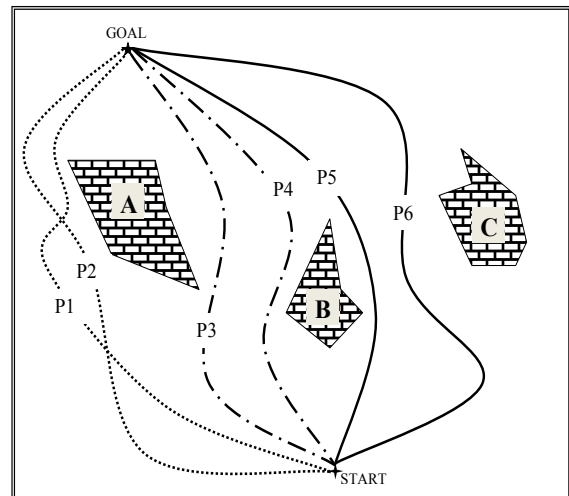


Figure 1: Conceptual and Particular Path Plans

In the SBC approach the problem is formulated such that each concept is represented by a set of particular solutions. The concept selection and ordering problem is transformed into a problem of comparing particular solutions from all the concepts.

We note that most SBC studies concentrate on having the search results prior to a human-based selection process. Given the subjective nature of concept selection, the inherent uncertainties and partial information, adding in-process human interaction to SBCs techniques is desired [1]. To support human interaction during the SBC search, it appears most beneficial to have visualization and signalling elements. Yet, adding such potentially crucial elements has hardly been studied in the context of the SBC approach.

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Past studies, e.g., [2], on interactive evolutionary search of SBCs concentrated on multi-objective search and on how decision makers can interfere with the search. The motivation for such studies was to develop algorithms in which human's preferences towards concepts and sub-concepts are included as weights in the fitness evaluations. In such studies it has been assumed that the current (temporary) fronts of the concepts are presented, in a shared objective space to support the interactive decision making.

Here both the problem and the method are different from past studies such as [2]. To simplify this early study on visualization and signaling for the SBC approach, we restrict the problem to a single objective one. Our focus here is on supporting the interactive process by providing visualization not only of the temporal (current) data on the performances at the shown generation, as in [2], but also of the performance history and of the predicted performance. As demonstrated here, adding such elements, and in particular the latter, is most useful for the interactive process. The addition of a predictor, to extrapolate the ranking of the concepts, enables the inclusion of a warning signal to humans, which alerts their attention to important suggestions made by the computer. The motivation for the current study is to provide a mean to overcome the "curse of dimensionality," which is expected in the SBC approach when dealing with many concepts.

While restricted to a single-objective case, we add to this study a discussion on how the current approach could be extended to a multi-objective concept selection and ordering.

The rest of the paper is organized as follows. Section 2 provides a description of the problem, whereas Section 3 includes a detailed description of the search method. Section 4 demonstrates the procedure on a conceptual path planning problem, and Section 5 provides the conclusions from this study including some suggestions on its extension to the case of multi-objective search.

## 2. PROBLEM FORMULATION

The problem which is dealt with here is that of a competition among candidate concepts. Given a set of ' $m$ ' candidate concepts, the search goals are to find and order ' $s$ ' concepts that are superior to the other ' $m - s$ ' concepts, where ' $s < m$ '.

In a single objective case the superiority and order is based on a single performance measure of the particular solutions of the concepts. Figure 2 helps to describe the problem.

A subset of ' $s$ ' superior concepts is sought from the search set  $S$  of ' $m$ ' candidate concepts. Let  $C_j$  denotes the  $j$ -th concept of  $S$ . The ' $m$ ' concepts of the search set are associated each with its own set  $P$  of particular solutions. The particular solutions are associated each with its performance value. Consider concept  $C_j$  with its associated set  $\mathbb{P}_j$  of particular solutions. Let the  $i$ -th solution of the  $j$ -th concept be denoted as  $P_i^j$  with the associated performance value  $V_i^j$ . Let  $P_*^j$  be the best solution among all solutions of the  $j$ -th concept, based on its value  $V_*^j$ .

Let each concept  $C_j$  be evaluated based on a concept value  $v_j$ . There are many ways to define a concept value based on the

values of its associated solutions. Here we define the concept value  $v_j$  as equal to  $V_*^j$ . With the above concept evaluation method the goal of finding an ordered set (of cardinality ' $s$ ') of superior concepts are met by ordering (or ranking) the concepts according to their  $v_j = V_*^j$  values, starting with the best performed concept ( $rank = 1$ ) and ending with the worst performed one ( $rank = 'm'$ ). In the case of a subgroup of concepts with identical performance value, all these concepts are randomly ranked by the subsequent order, relative to those which have been already ranked. A concept  $C_j$  is considered superior if its rank meets the following requirement:

$$rank[C_j] \leq s \mid j = \{1, 2, \dots, m\}.$$

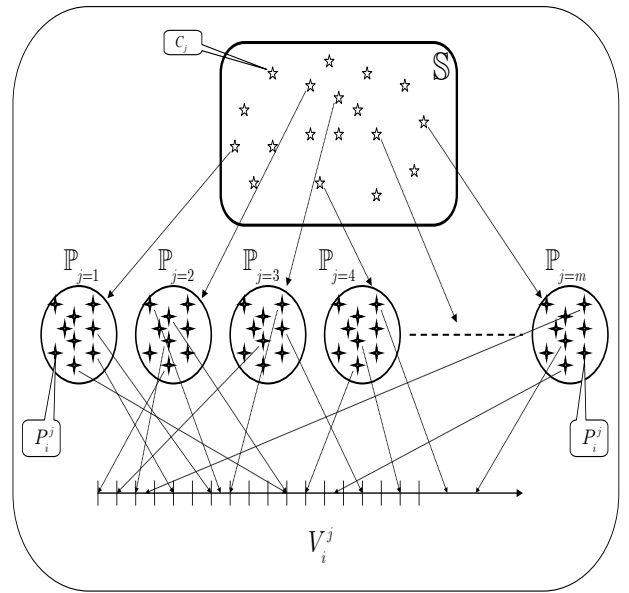


Figure 2: The SBCs problem description

In the current evolutionary conceptual path planning demonstration, superiority and order of concepts are based on the evaluation of particular paths of the conceptual path plans. The particular paths used in the evolutionary process are hereby termed Concept-Representing-Paths (CRP). Currently, the CRP is real-coded based on a piecewise linear path shape. Evaluating the CRP is based on its length in conjunction with penalties to ensure compatibility with the feasible space of the associated concept.

Due to the scope of this paper, details of the demonstration are restricted primarily to the interactivity aspects, and the interested reader can get more details on other issues, such as the penalties used here, directly from the authors.

## 3. CONCEPT-BASED SEARCH

### 3.1 Search Outline

The entire Concept-Based Search (CBS) procedure is schematically depicted in figure 3. The search starts with an initial

parent population for each of the concepts. Next, the procedure involves a primary loop called "generation-loop", at which all concepts are simultaneously optimized through a generation-sequence. The generation-loop includes a secondary loop, called "concept-loop", in which each concept is evaluated based on the accumulated information up to the particular generation. During the search, at some predefined check-points, all concepts are being ranked and then interactively categorized. The interactive categorization procedure supports the proper distribution of the computational resources among the concepts. Following the generation-loop, when a termination criterion is met, the obtained superior concepts are presented. Further details are given below.

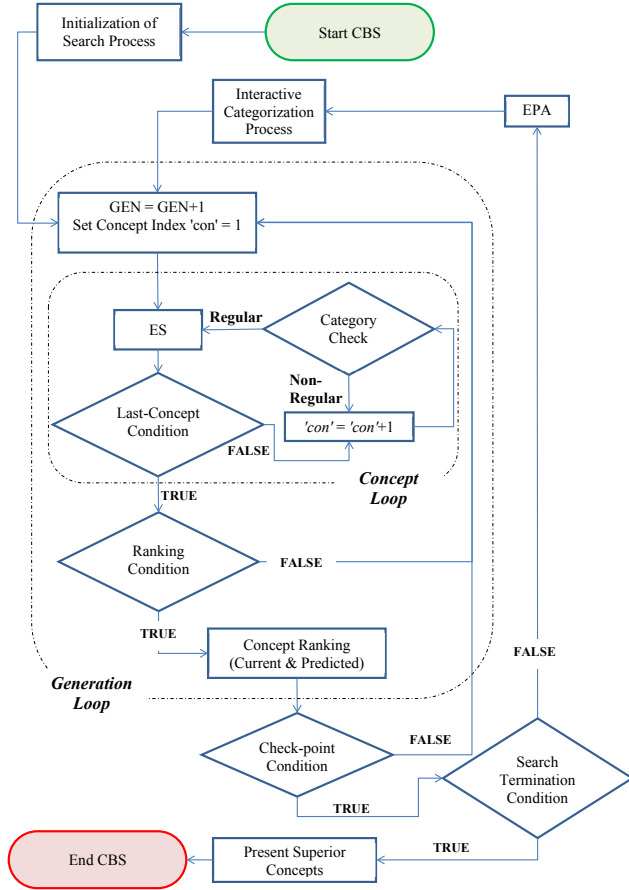


Figure 3: Concept-based Search Flowchart

### 3.2 Concept-loop

Following an initialization stage, the concept-loop is carried out for each concept at each generation with the exclusion of non-regular concepts, which are defined below. The concept loop includes the following three elements: 1. *Evolutionary Computation (EC) Core*; 2. *Last-Concept Condition*; 3. *Concept Category Check*.

**EC core** - For the EC core different search mechanism can be used. In the current implementation we use Evolution Strategies (ES), [3], and in particular (1,λ)-ES. The ES process results in selecting the best offspring of the concept as a new single parent for the next generation.

**Last-Concept Condition** - The last-concept condition verifies that all interesting concepts have been treated at the current

generation. The algorithm remains within the concept-loop as long as this condition remains unsatisfied.

**Concept Category Check** - As detailed in sub-section 3.4 below, all concepts are interactively assigned with one of the four following categories: 1. *Converged*; 2. *Detained*; 3. *Eliminated*; 4. *Regular*. Concept category check verifies that only concepts that have been categorized as regular undergo an optimization process at the current generation by the ES. All other concept types (herby termed *non-regular* concepts) including converged, detained and eliminated, are skipped.

Once per ranking-interval (further explained under "*Ranking Condition*" in sub-section 3.3) all non-regular concepts are evaluated with enlarged mutant population (in this work we use five times the original mutant population for each non-regular concept). This procedure makes it possible to correct categorization faults, which may occur during the process due to temporary stagnation of concept's convergence.

### 3.3 Generation-loop

During a generation-loop all concepts are searched, evaluated and ranked, until the termination criteria are met. In addition to the concept-loop, the generation loop includes *Ranking Condition*, and *Concept Ranking Procedure*. These are further detailed below.

**Ranking Condition** - We divide the entire set of ES generations into several *ranking-intervals*; each such ranking-interval consists of '*t*' generations. Meeting the ranking condition means the end of the current ranking-interval and the beginning of the following one. At the end of each ranking-interval all interesting concepts undergo a ranking procedure (as further described below). The ranking condition is checked at the end of each generation. In this work we use '*t*' = 50.

**Concept Ranking Procedure** - Two types of ranks are calculated for each concept. The first rank type is termed the *current-rank* and the second type is termed the *predicted-rank*. These ranks are needed for two reasons: 1. to support the search termination criteria (as further described below under "*Search Termination Condition*" in sub-section 3.5), and 2. to support concept categorization (as further described below under "*Elimination Proposition Algorithm*" in sub-section 3.4).

The current-rank is decided by ordering the concepts based on the fitness  $V_*^j$  whereas the predicted-rank is decided by ordering the concepts based on a predicted fitness  $W_*^j$ .

The predicted fitness of concept '*j*' at the specific generation '*Gen*' is calculated by a special procedure involving an estimation of the rate of change of the fitness value of the CRP:

$$C\_rate = 1 - \frac{V_*^j(Gen - t) - V_*^j(Gen)}{V_*^j(Gen - t)} = \frac{V_*^j(Gen)}{V_*^j(Gen - t)}$$

Where:

'*Gen*' - the index of the current generation.

$V_*^j(Gen)$  - fitness value of CRP of concept '*j*' at generation '*Gen*'.

'*t*' - Ranking interval (as described above under "*Ranking Condition*" above).

$V_*^j(Gen - t)$  - fitness value of CRP of concept 'j' at generation 'Gen-t'.

Note that the rate of change ( $C\_rate$ ), which indicates the convergence rate, is calculated based not on two subsequent generations but on the difference over a range of generations. This difference is employed here because the convergence behavior is unstable between two subsequent generations and does not reveal any convergence trend. The calculated rate of change is assumed to be constant (for a specific concept) from the current check-point till the termination of the search process. The predictor calculates, at the current generation ('Gen' = j), the predicted fitness,  $W_*^j$  for the last generation ' $Gen_{max}$ ', using the following non-linear extrapolation formula:

$$W_*^j(Gen) = V_*^j(Gen) \times C\_rate^{\frac{Gen_{max} - Gen}{t}}$$

Where:

' $Gen_{max}$ ' - predefined number of generations till ES termination (set by the user during the initialization).

It should be noted that optimizing the predictor was not a goal of this study, and such optimization is left for future research.

### 3.4 Concept Categorization

The concept categorization procedure divides all concepts into four categories. This procedure includes *Check-Point Condition*, *Elimination Proposition Algorithm (EPA)* and *Interactive Categorization Process*. These are further detailed below.

*Check-Point Condition*- The concepts are categorized only at predefined stages of the optimization sequence. These stages are hereby termed as *check-points*. The check-point condition is inspected at the end of each generation to determine whether it is a time for all the concepts to be categorized. In this work check-points are also aligned with ranking-interval (see sub-section 3.3), meaning one check-point is located at every 't' generations.

*Elimination Proposition Algorithm* - To reduce computational efforts an *Elimination-Proposition Algorithm (EPA)* is designed to estimate the concepts chances to become one of the 's' superior concepts. The concepts with lower chances are proposed to be eliminated. First, the EPA creates a subset of up to '2s' concepts. This subset contains the 's' best performed concepts, as ranked by the 'current' rank operator, and up to 's' additional concepts, which have been predicted as superior concepts by the predicted rank operator. The above subset is hereby termed as the *current superior group*. Second, the EPA finds a subset of *worst* concepts based on the concepts' order by the 'current' rank starting from the worst rank. The cardinality of the worst-concept-subset is based on a predefined percentage (in this work 10% - 20%) of the regular concepts. This percentage hereby termed as *worst-subset percentage*. In addition it checks whether the concepts in this subset are not a part of the *current superior group*. If for several predefined number of subsequent check-points a particular concept belongs to the worst subset and is not included within the current superior group, it is suggested by the EPA to be eliminated from the optimization process. The check-point at which such a proposition is made is hereby termed as a *warning-point*. In such a point a warning signal alerts the attention of the

humans in charge of interactivity. The EPA suggestion is presented to the human decision-makers who subjectively decide whether to follow the computer's suggestion and eliminate the proposed concept(s). At this stage they may perform one (or more) of the following actions and categorizations:

- Permanently eliminate the proposed concept(s). Such a concept is categorized as eliminated.
- Continue optimization of the proposed concepts. Such a concept is categorized as regular.
- Detain the proposed concept(s) for several generations to be defined by the operator. Such a concept is categorized as detained.
- Eliminate additional concepts that are not suggested by EPA (also categorized as eliminated).
- Detain additional (not suggested) concepts for several generations (also categorized as detained).

There is an additional category, called converged category, to which a concept can be assigned automatically. The assignment to converged category involves any concept which for a predefined number of subsequent check-points meets the following criterion:

$$C\_rate < C\_rate_{min}$$

Where:

$C\_rate_{min}$  - convergence rate at which the searched path is considered to converge. This is a problem dependent value, subjectively provided by the user.

The categorization process assigns all concepts to one of the following four categories: the eliminated category, the detained category, the converged category or the regular category. Concepts which have been categorized as terminated, detained or converged are termed as a non-regular concepts (the rest are categorized as regular).

### 3.5 Search Termination

The entire optimization procedure is performed until one of the following two conditions is met:

- A pre-defined number of generations have been executed ( $Gen = Gen_{max}$ ).
- A final-convergence criterion is met as further discussed below (examined at each check-point).

The final-convergence criterion is met when all of the following three requirements are met for a predefined number of subsequent check-points:

- The 's' superior current ranks are occupied by the same concepts and in the same order.
- The predicted ranks of the 's' superior concepts are equal to their current ranks.
- When ranking the concepts, 's' superior concepts are converged.

## 4. NUMERICAL STUDY

### 4.1 Test Description

The purpose of this test is to demonstrate an interactive search on polygonal-obstacles scenario and to compare it with a non-

interactive search approach and with a reference solution. The problem is to select and order three superior concepts out of six candidate ones. An illustration of the six candidate concepts is provided in figure 4.

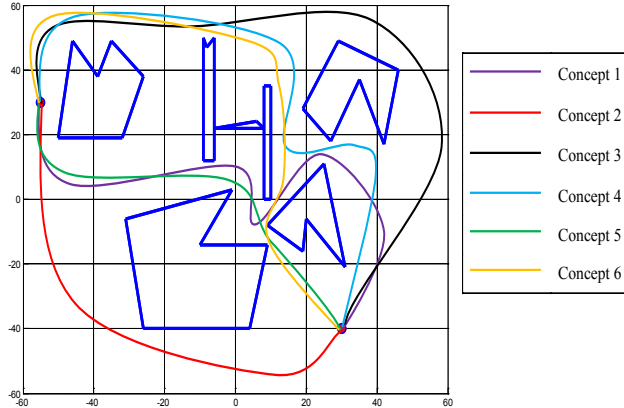


Figure 4: Illustration of Concepts

Each concept is schematically represented by a curve (a path) that hints at the common features of the particular paths which constitute the concept. The set of rules, which describe the position of the representative curve, relative to the obstacles, is common to all paths of the represented concept. For example all paths that belong to concept # 2 must go "below" all the obstacles. In the actual implementation the CRP are represented by piecewise linear curves, as described in section 2.

## 4.2 Test Results

The CRP of the detected 3 superior concepts are shown in figure 5, as obtained by the interactive approach.

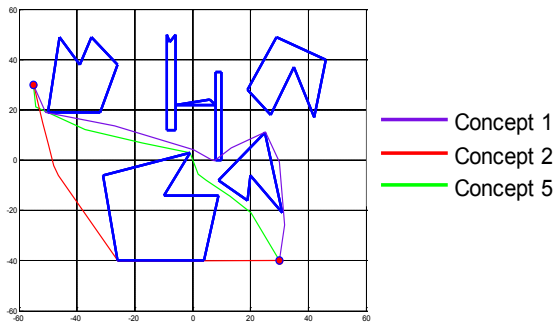


Figure 5: Superior Concepts Layout

Table 1 shows some reference data. It includes the shortest path fitness per each concept as calculated using the method of visibility graphs [4]. Table 1 also shows as a reference, per each concept, the median of the number of evaluations it takes to independently search within each concept and converge to the optimal solution, with no human interaction (calculated using 30

independent runs per each concept). The later data suggest, for example, that concept # 6 is hardest to converge.

Table 1: Reference Data

Concept #	Shortest path fitness	Eval. Median
1	146.2	6751
2	131.8	5090
3	197	3500
4	163.4	3762
5	116.7	4027
6	164.9	8157

A summary of the search events is presented in figure 6. The horizontal axis shows the check-point number, and the vertical axis shows the absolute values of the CRP fitness (absolute values reflect penalized length). Six solid lines are shown; one per each of the candidate concepts. Circular marks are located on top of the solid lines. They represent the warning-points. In addition, on top of the solid lines "cross" marks are also located, representing the elimination-points. As seen from the figure, there has been five warning points during the evolutionary session.

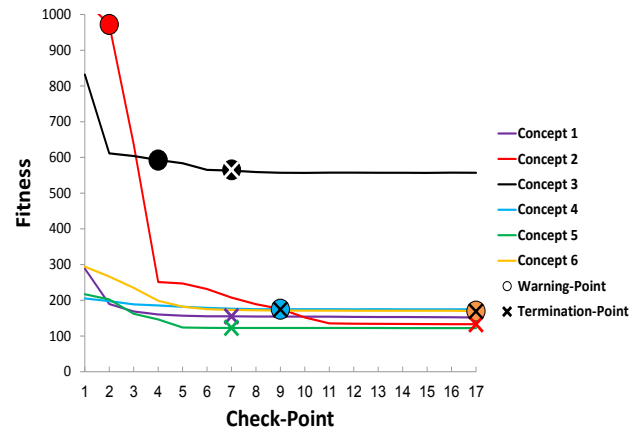


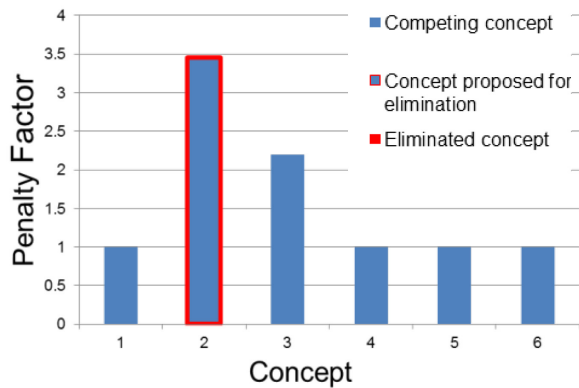
Figure 6: Summary of Search Events

The details of the computer suggestions and human actions, at all warning points are given in table 2. For example, very early in the search, at warning-point # 1 (check-point # 2), it was suggested that concept # 2 could be eliminated from the search. This suggestion is certainly a wrong one, and is due to bad predictions at the early stage of the search. It is also clear from both figure 6 and table 2 that the wrong suggestion is not repeated in the subsequent warning points. In fact concept # 2 is found to be a superior concept.

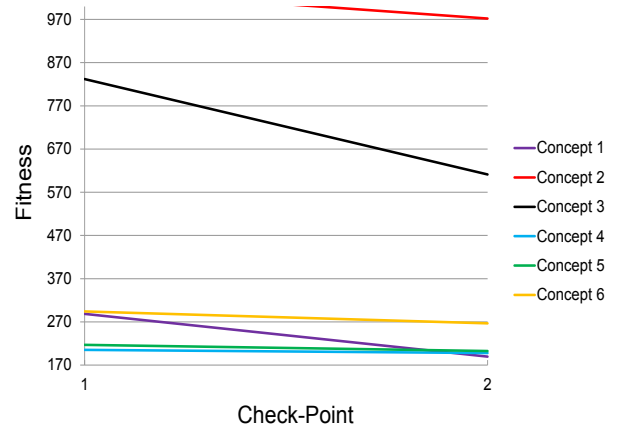
**Table 2: Computer Suggestions and Human Actions**

Warning Point number	Computer Suggestion	Human Action
1	Eliminate concept #2	None
2	Eliminate concept #3	None
3	Eliminate concept #3	Eliminate Concepts # 1,3 & 5
4	Eliminate concept #4	Eliminate Concept # 4 Detain Concept #6 for 300 generations
5	Eliminate concept #6	Eliminate Concept # 6

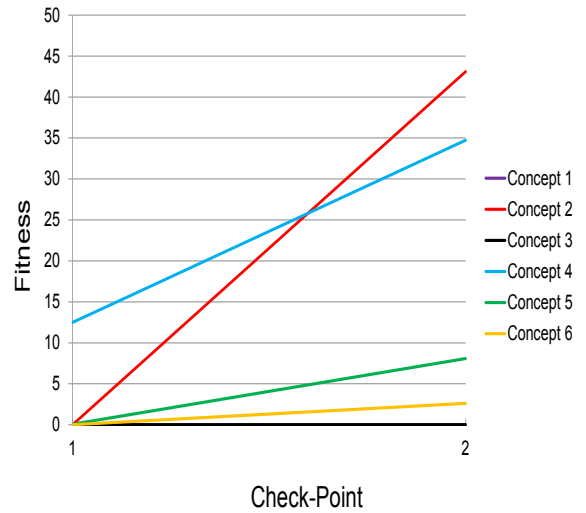
The visualization of the search information at the first warning point included the best path of each concept as obtained at that point, as well as the data, which is presented in figures 7-9 and in table 3. From the data, such as in figure 7, it is clear that the suggestion is based on a wrong comparison due to the high level of penalty, which is associated with concept #2 as compared with the other concepts (penalty factor of 1 means no penalty).



**Figure 7: CRP Penalty Factor at Warning-point 1**



**Figure 8: CRP Fitness at Warning-point 1**

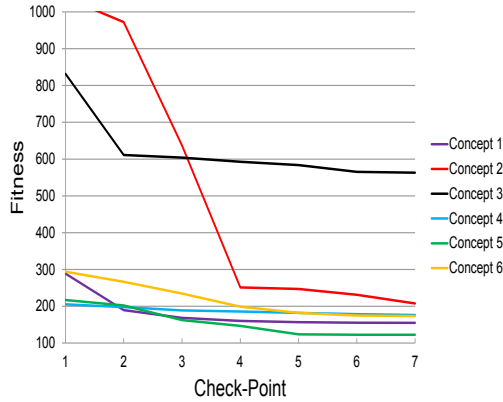


**Figure 9: Predicted CRP Fitness at Warning-point 1**

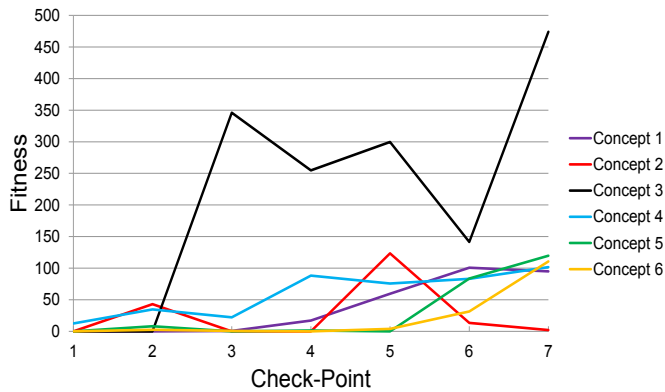
**Table 3: CRP Fitness and Concept Order at Warning-point 1**

Order	Concept #		CRP fitness	
	Current	Predicted	Current	Predicted
1	1	1	189.6	5.0E-07
2	4	3	197.7	0.0003
3	5	6	202.5	2.6
4	6	5	266.6	8.0
5	3	4	611.1	34.7
6	2	2	972.0	43.1

At warning point # 2 a suggestion is made to eliminate concept # 3, and in the subsequent warning-point the same suggestion is repeated (see table 2). To understand the human decisions at the later point, the data, which was presented at warning-point # 3, should be considered.

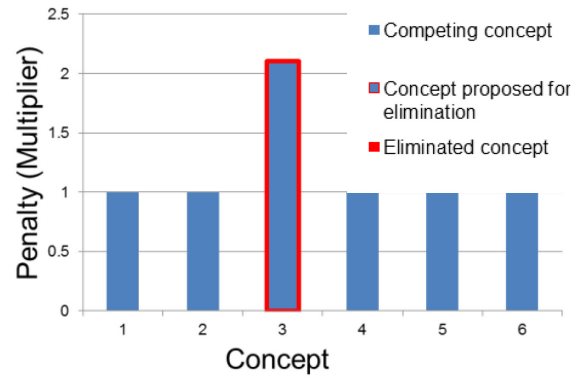


**Figure 10: CRP Fitness at Warning-point 3**



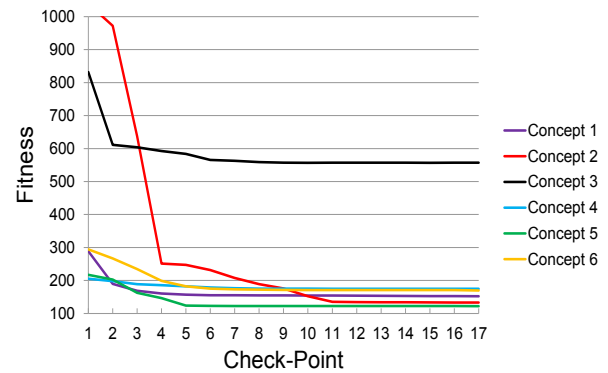
**Figure 11: Predicted CRP Fitness at Warning-point 3**

It is quite clear from the information in figures 10 and 11 that the suggestion to eliminate concept #3 is based on persistent data. Yet, it should be considered with care as revealed from figure 12. It is quite clear that at this point the calculations are based on a penalized fitness of concept #3, as compared with non-penalized fitness in the rest of the concepts. Yet the magnitude of both the calculated and predicted fitness of concept #3, as seen in figures 10 and 11 suggests that concept #3 indeed is not a good one when compared with the others. In the current algorithm the elimination suggestions made by the computer refer only to bad concepts. Yet, humans may decide to eliminate a good concept from the search to save computational efforts. This is the case, for example with concepts 5 and 1, which are subjectively eliminated. Such a decision can be based on the observation of the fitness curves from check point 5 till 7 as seen in figure 10.

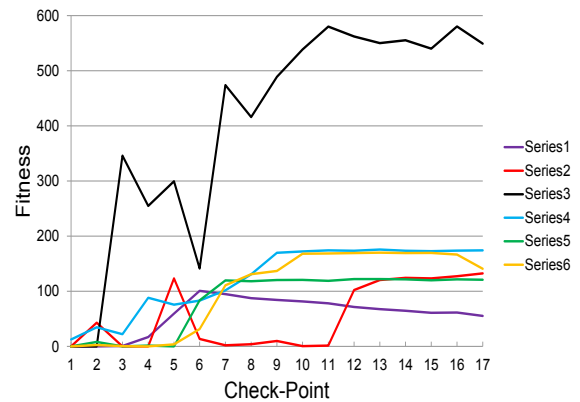


**Figure 12: CRP Penalty Factor at Warning-point 3**

Data at last warning-point # 5 (check-point 17) is provided in figures 13-15 and in table 4.



**Figure 13: CRP Fitness at Warning-point 5**



**Figure 14: Predicted CRP Fitness at Warning-point 5**

It is clear from figures 13 and 14 that at this stage of the search the results are converging and no major changes are expected.



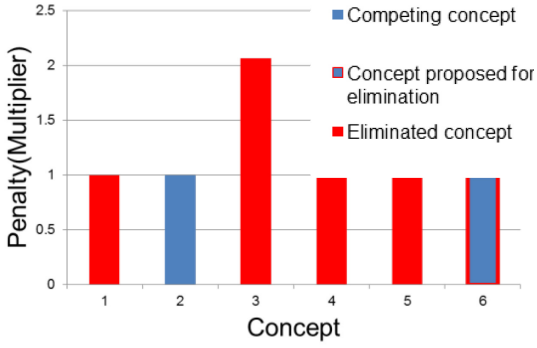


Figure 15: CRP Penalty Factor at Warning-point 5

Table 4: CRP Fitness and Concept Order at Warning-point 5

Order	Concept #		CRP fitness	
	Current	Pred.	Current	Pred.
1	5	1	122.2	48.6
2	2	5	133.1	121.2
3	1	2	151.1	133.1
4	6	6	169.4	165.5
5	4	4	174.9	176.1
6	3	3	556.7	562.0

Table 5: Summary of Tests Variables

<b>Gen<sub>max</sub></b>	1500
<b>Number of ES Parents (<math>\mu</math>)</b>	1
<b>Number of ES Mutants (<math>\lambda</math>)</b>	5
<b>ES Initial <math>\sigma</math></b>	0.1
<b>C<sub>rate</sub><sub>min</sub></b>	0.05
<b>Worst-Subset Percentage</b>	10%
<b>Ranking-Interval (t)</b>	50

It is quite clear from the presented information in figure 15 that if the suggestion is to be followed then the only concept left for further search is concept # 2. In essence this would mean that the search is over, although further search within concept # 2 is permitted for finer evaluation of the best path within the concept. Comparing the data of table 4 with the reference data of table 1 it is clear that the process resulted in the proper selection and order of the three superior concepts (5, 2 and 1)

For the presented test the use of an independent run per each concept, to obtain similar level of results, required over **31,000 evaluations** (see table 1), whereas the interactive approach required about **12,500 evaluations**. The above numbers are just indicative to the current session. Yet, it is a general rule that early elimination of concepts from the search process has a substantial effect on the required number of evaluations.

Table 5 provides the search parameters used in the study. For further details the reader is referred to the comment on the implementation details at the end of section 2.

## 5. CONCLUSIONS

This paper deals with warning signals and visualization for interactive evolutionary search and selection of conceptual solutions. The suggested procedure aims to support overcoming the curse of dimensionality in such concept-based problems. The elimination of concepts during the search has a significant effect on the required number of evaluations. The visualization of the search data helps rational elimination of concepts and supports the proper exploitation of computational resources. The predictor used here is basic and not an optimal one. Future work should include an investigation on the use of various predictors and supportive machine learning techniques.

In general, concept selection is based on multi-objective evaluation. If a Pareto-approach is to be used the current visualization procedure has to be revised. It would be impractical to show a trace of fronts as a replacement to the trace of fitness used here. Yet, traces of performance measures of the fronts are a conceivable replacement. Similarly, predicted values of the fronts' measures can be calculated. Future work on visualization for interactive multi-objective evolutionary search and selection of conceptual solutions is expected to follow such ideas.

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