

Hybrid Representation and Reasoning for Constructivism-based Darwinian Learners by a Multi-Competence Cybernetic Approach

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Abstract—In this study a Darwinian knowledge acquisition approach is proposed. The problem and solution paradigm are given, with detailed explanations on the rationale for the proposed learning methodology. Inherent to the presented problem paradigm is hybrid knowledge representation and reasoning, involving particular and conceptual solutions. It is concluded that the proposed paradigm should support self-learning of robots to conceptually plan.

I. INTRODUCTION

THIS study considers a special form of deliberation, involving planning and constructivism learning. In particular we focus on deliberation about conceptual and particular solutions for robotic planning problems. We acknowledge that our current work is not on a fully autonomous version. Rather, as discussed in section 5, it is assumed that prior to the self-learning stage there is an initial stage of knowledge acquisition. Using learning theories, which are briefly presented in section 2, our focus could be described as on a constructivism-based process that starts after an assumed cognitivism-based process.

In the quest to develop cognitive robots, bio-inspired techniques appear to be significant. Soft computing is a well established bio-inspired school of thought, which studies different types of hybridization of Artificial Neural Networks (ANN), Fuzzy Logic (FL), and Evolutionary Computation (EC) (e.g., [1]). The resulting techniques are commonly referred to as 'intelligent hybrid systems.' For the scope of this paper, we have found EC to be most useful, with some reference to FL.

To understand the notions of particular versus conceptual plans, in a multi-objective planning problem, consider figure 1. It schematically depicts a squared environment, with an internal oval obstacle, and with a potential for explosion at the left of the obstacle. The 4-point and 5-point stars mark the start and goal states, respectively. North is considered as the top of the environment. If the potential to explosion is zero, and if the shortest-path is considered, then the straight line from start to goal should be applied. If the risk for explosion is

extremely high, and the length of the path is of no importance, then the optimal path is different.

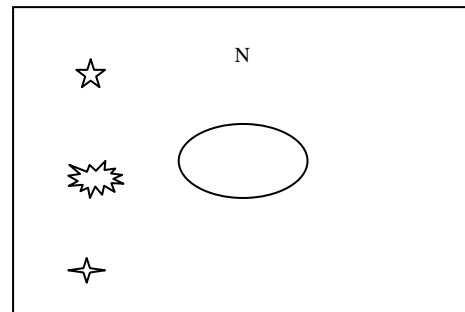


Figure 1: Multi-objective Planning

In such a case it is likely that one would prefer to go southward as much as possible, and then to the east as much as possible, and stay there! With the goal-state in mind, to reduce risk, it would be wise to continue along the east side towards the north and then stay along the north side until reaching a point as close as possible to the goal. From there a straight line to the south should lead the robot to the goal. The later description of the safest-plan (but longest-plan) can be represented as a piecewise linear curve, mostly along the boundaries, which constitutes a particular solution to the planning problem. The above two extreme situations can be argued. Cost of executing the plan might be too high and the risk of explosion might be considered as very low. In such a case, a Pareto-approach to explore different alternatives is wise.

Above, we have used particular solutions to describe the possible plans. Yet, we can re-discuss the planning in terms of conceptual plans. Consider a conceptual plan as going left to the obstacle to reach the goal. Such a fuzzy description implicitly contains infinite particular plans. With either fuzzy or crisp representations of parts of the environment, different conceptual plans could be generated and considered.

The idea to use of a Pareto approach for robotic path planning applications is not new (e.g., [2]). Furthermore, using a Pareto approach for conceptual planning in application areas such as robotics and A-life has been recently suggested [3]. The later study provides a concrete example of multi-objective conceptual path-planning. Yet, in [3] and related works, the method is restricted to human-

Manuscript received May, 2011.

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machine interaction. In the current paper, for the first time, we propose problem and solution paradigm that extend ideas such as in [3], to self-learning to plan, by robots. In a nutshell, the proposed approach uses the values associated with particular path plans to evaluate conceptual plans to be memorized. In parallel to describing the suggested methodology, we highlight the fact that it requires hybrid representation and reasoning.

Figure 2 summarizes some of the elements involved in our study. The left side contains computer-related techniques, and the right side shows human-related issues. The fusion of ideas, as depicted in figure 2, is expected to support the development needs of cognitive robots with creative planning capabilities. The following sections 2 and 3 describe and explain the inspiration and motivation for this study. These are followed by section 4, which provides a presentation of a paradigm of problems that is proposed here for self-learning to plan. A discussion on the proposed methodology is given in section 5. Finally section 6 summarizes this paper.

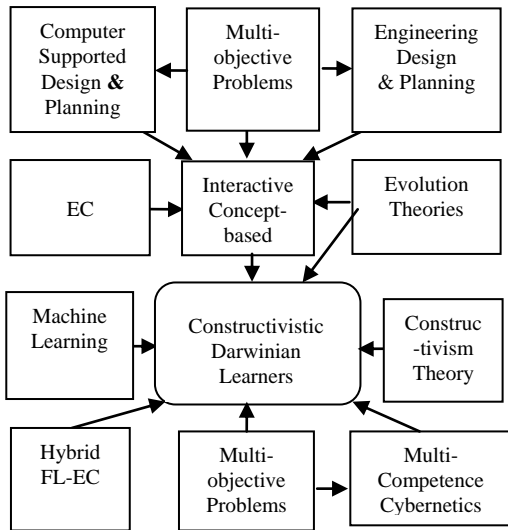


Figure 2: Fusion of Ideas

II. LEARNING

Constructivism is considered, in education, as a learning theory, which focuses on the assumption that learning is an active process of constructing knowledge by the learner, rather than just acquiring it from the teacher. The term constructivism, as employed in ML and robotics, is commonly associated with neuro-development. In contrast, here we refer to constructivism as in education. Given the focus of this paper on deliberation about planning, constructivism becomes a major source of inspiration (as depicted in the right side of figure 2). In our quest for ideas and tools to support the development of creative learners,

we are also inspired from other resources. These are discussed below.

III. CREATIVE DESIGN AND PLANNING

Einstein and Infeld, [4], have pointed out that *"The formulation of a problem is often more essential than its solution, which may be merely a matter of mathematical or experimental skill. To raise new questions, new possibilities, to regard old problems from a new angle, requires creative imagination and marks real advance in science."* In some sense scientific work resembles engineering design and planning. The scientist must not only know how to plan and execute her actions, but also to constantly reconsider her goal(s). It is our conviction that the above observation holds also for creative engineering design and planning. In other words, we replace *"marks real advances in science,"* with *supports real advance in engineering and science.* This conviction serves as a general motivation for our study, which involves 'creative imagination' that includes creation of 'new questions' (problems) and new solutions in the context of planning. Engineering design is often considered as an ill-defined problem. One may say that engineering involves *creative imagination* both for posing the ill-defined iterative problem and for solving it.

Conceptual design is an early stage of the engineering design process, in which creative imagination is essential. The a design concept (conceptual solution) is different from the final product. Design concepts commonly involve fuzzy ideas about a presumably feasible and useful product. Conceptual solutions are described by the engineers in abstractive terms (commonly in linguistic terms, and possibly also with sketches). During conceptual design engineers generate, discuss, and evaluate different concepts, and finally select a preferred concept.

One may view the conceptual design stage as an attempt of the engineers to reduce the search difficulty from a search in an infinite space of solutions into a search within the selected concept. The reduced space is an implicit set of similar solutions, which are perceived as a conceptual solution. A major question to be raised is how engineers mentally create a partition of a feasible space of solutions, without a grasp on the infinite particular solutions that are implicitly contained within the generated concepts. We can only speculate on the answer based on cognitive theory. Another major question is how engineers evaluate the different concepts and how they select the preferred one. Due to their nature, conceptual solutions are extremely hard to evaluate. Selecting the preferred concept is a job for experts, and although rationalized by different methods, it remains a subjective task. Design and planning have much in common; hence, we assume that the above discussion on design is of relevance also to planning. All of this implies

that if one wants to use a bio-inspired concept-based approach to develop a learner with concept-based planning capabilities, she should overcome a magnitude of difficulties including: ill-defined problem, subjective evaluation of concepts, and generation of concepts. In this study we suggest a possible framework to tackle some of these issues. Paramount to our proposal, as depicted in figure 2, is a suggested shift from a recently introduced interactive human computer concept-based approach [3, 5], which is shortly termed as the concept-based approach. Although not restricted to Pareto-optimality and EC, the concept-based approach has been primarily studied using a Pareto-based multi-objective EC approach, as well as crisp sets to describe the concepts. The concept-based approach serves as a source of inspiration for the current investigation. This is depicted in figure 2, by the box titled Interactive Concept-based Multi-objective Planning.

Evolution theory is an important source of inspiration for the generation of creative solutions and for our study (as depicted in the right side of figure 2). Studies on both A-life and Engineering have demonstrated the power of EC to provide bio-plausible and bio-inspired creative solutions (e.g., [6]). Moshaiov provides, in [7], a unified framework, which has been termed multi-competence cybernetics, to consider the evolution of both biological and artificial systems from a multi-objective/multi-fitness viewpoint. Multi-competence cybernetics is another source of inspiration and motivation for the current study on constructivism-based Darwinian learner (as depicted in the right side of figure 2).

Generating and comparing solutions are key issues when dealing with deliberation in self-learning to plan. Hence, EC is a major candidate to support our efforts (as depicted in the left side of figure 2). However, in its customary set-up, the utilization of EC for conceptual design is somewhat restricted since that it does not allow for a hybrid exploration of particular and conceptual solutions.

In traditional Multi-objective Optimization Problems (MOPs) optimal elements of the decision space are to be found. In such a case, defining optimality is based on the components of the one-to-one mapping onto objective space of the solutions. However, there is no unique way to compare solutions based on these components; hence, the notion of "optimal solutions" requires a formal statement of the comparison method, [8]. A Pareto approach allows postponing the decision on objective preference while still finding an optimal set of solutions. In Pareto-based techniques, individual solutions are compared by a domination relation without any bias toward certain components of their mapping to objective space.

The apparent main advantage of a Pareto approach is that it provides a broad set of optimal solutions to choose from, as well as an insight on the tradeoffs involved in such a

selection. Commonly, in planning, a final plan to be executed is sought (a particular solution, rather than a conceptual one). Hence the use of a Pareto approach for planning relates to an intermediate stage when objectives are still negotiable. It should be noted, with this respect, that self-learning to plan is different from planning, as it constitutes a pre-planning stage. By its nature Pareto-optimality supports deliberation about solutions before any particular selection. This makes it suitable to support a cognitive creature in reasoning about different alternative solutions to be memorized. Clearly the mathematical ideas of MOPs and Pareto-optimality are another source of inspiration for the proposed learner, as depicted in figure 2.

Planning, as commonly understood by classical AI researchers, is about finding, under some constraints, a feasible sequence of actions to achieve a goal-state from a start-state. In trajectory and in path planning, which are common in robotics, the focus is on directly finding a list of feasible neighboring states (either finite or infinite) from start to goal, under the assumption that the required list of actions is achievable. In addition to categorizing planning problems as action-centered (as in AI) or state-centered (as in path planning), planning problems are commonly divided into three types. The first is the regular type in which a feasible plan is sought. The second is the optimal type in which the space of feasible plans is searched for the optimal plan under some criterion or criteria. The third is the robust type in which a robust plan is sought under some form of uncertainties. With this respect, Pareto-optimal planning can be viewed as a robust planning with uncertainties about the planners' objective preferences. For self-learning to plan it is conceivable that the learning should amount in some sense to memorizing robust conceptual plans. However, what constitutes a robust concept is a matter for a discussion. The concept-based approach provides ideas how to compare and select concepts in multi-objective problems, based on the performances of particular solutions that are associated with the concepts. The following section contains a proposed general problem paradigm for comparing conceptual solutions in MOPs.

IV. PROBLEM PARADIGM

As a part of its general scope, this study aims to modify the concept-based approach from an interactive one, using crisp sets, to an automated one, using fuzzy sets. The modification is proposed for the development of Constructivism-based Darwinian Learners for planning.

The concept-based approach, concerns a non-traditional optimization problem and the use of set-based concept representation. In contrast to traditional Multi-objective Optimization Problems (MOPs), which deals with "optimal solutions," the concept-based approach involves the search

for "optimal sets." In other words, each concept is represented as a set of particular solutions of some implicit or explicit similarity, and the search is about optimal concepts. Three major optimization strategies have appeared in the literature on the concept-based approach, namely the s-Pareto strategy, the optimality versus variability strategy, and a relaxed Pareto strategy ([3, 9]). This reflects the fact that there is no agreement on what constitutes an optimal set in such non-traditional multi-objective optimization. In the interactive approach it is assumed that the designers provide a graph of crisp-set-based conceptual solutions, and the associations to the particular solutions. In addition they provide the models on which the evaluation of particular and conceptual solutions are done. The computations amount to optimization of the concepts by way of the associated particular solutions and their calculated performances.

The following provides an extended view on the concept-based approach, as a general multi-criteria problem-paradigm. The proposed multi-criteria problem-paradigm consists of a main-problem and an auxiliary-problem. The main-problem-paradigm deals with finding a set of optimal concepts and it is described as follows:

Consider a set C of candidate-concepts, find for any m -th candidate-concept, S_m its evaluation-set, E_m , as described in the auxiliary-problem. Next, using the admissible candidate-sets, and given a mapping $F' : E \rightarrow Y'$, where $E = \bigcup_m E_m$, find the set

$C^* \subseteq C$ of the "optimal-concepts," taking into consideration the multi-criteria performances of the elements of the evaluation-sets in Y' .

Clearly, the above problem description is not well-defined and requires further clarifications. This is in accordance with the nature of the design and planning processes is described. In contrast to traditional MOPs, in the current problem the entities (candidate-concepts) to be compared are not directly mapped onto an objective space, but generally have, each via its members, a one-to-many mapping onto the multi-criteria space, where members of the candidate-sets can be compared. The above problem, when considered in the context of Pareto-optimality, means that we wish, without necessarily specifying criteria preferences (possibly delaying preference selection), to find an optimal concept or concepts, from the "candidate-concepts" without necessarily selecting particular members of the concepts (possibly delaying member selection). In other words our intention is not to find optimal particular solutions as in traditional MOPs, but to find, the "optimal-concepts" of C . In conjunction with learning, such optimal concepts might be considered useful to memorize.

To fully define the above main-problem one needs to provide well-defined criteria/procedures that unfold the meaning of "optimal-concepts," and of "taking into consideration.....," which appear in the above description. Since that there could be different criteria/procedures associated with the above, we prefer using the term main-problem-paradigm rather than main-problem. The word paradigm hints at the generic characteristics of the proposed problem description, which encompasses different types of non-traditional MOPs.

Next, we amend the above problem description as follows. For each of all the candidate-concepts, $S_m \in C$, let its feasible-set be denoted X_m , such that $X_m \subseteq S_m$ includes all feasible elements of the m -th candidate-set. Since that the above description of the main-problem-paradigm does not refer to feasibility of the members of S_m , such a notion has to be clarified. It refers to constraints, which may be associated with the auxiliary-problem, as described further below. Next, let any i -th member of any X_m be denoted as $x_i^m \in X_m$, and let the set X be the union of the feasible members from all candidate-concepts, namely $X = \bigcup_m X_m$. Without losing generality on

non-feasible members of the candidate-sets, we assume that a one-to-one mapping $F : X \rightarrow Y$, is given, where F maps the members of X onto a mutual multi-objective space $Y \subseteq R^k$. In other words, for any $x_i^m \in X$ there exists one and only one associated vector $y_i^m \in Y$.

The above is illustrated in figure 3, which shows, from left to right, two candidate-concepts, $S_2=X_2$, and $S_3=X_3$, with 3, and 4 feasible members respectively. It also shows their mapping onto a mutual two-dimensional objective space Y . To increase the clarity of the figure, the vectors $y_i^m \in Y$ are shown as points (the tips of the mapping arrows) rather than arrows from the origin of objective space.

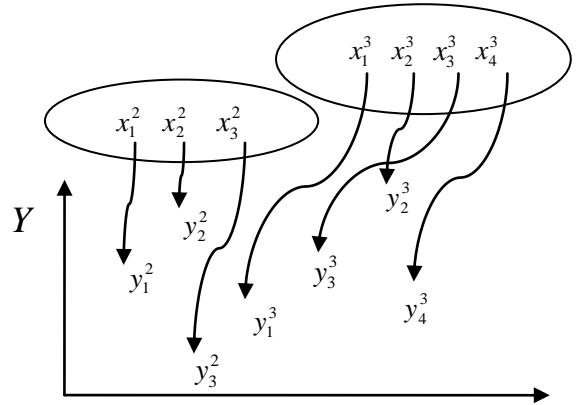


Fig. 3: Candidate-concepts and associated performances

We define, for any $S_m \in C$, an evaluation-set $E_m \subseteq X_m$, and let any i -th member of any E_m be denoted as $e_i^m \in E_m$. The evaluation-sets are defined as sub-sets of the associated feasible-sets to be the base for comparing the candidate-concepts in the main-problem. The following provides a description of the auxiliary-problem-paradigm, which aims at finding the evaluation-sets.

Given a set C of candidate-concepts, consider for each concept $S_m \in C$, the feasible-set $X_m \subseteq S_m$ resulting from possible constraints on using members of S_m . For a given mapping $F: X \rightarrow Y$, where $X = \bigcup_m X_m$, determine, for each $S_m \in C$, the evaluation-set E_m that consists of "passed-members" among the members of X_m , possibly considering their multi-criteria performances in Y .

In contrast to the main-problem-paradigm, the auxiliary-problem-paradigm resembles a traditional MOP, as it concerns solutions that have a one-to-one mapping onto objective space. Yet, it should be noted that the auxiliary-problem is not posed as an optimization problem. Similar to the main-problem description, the auxiliary-problem description is not well-defined. In other words, we need the criteria/procedures to unfold the meaning of "passed-members," and of the text that follows it in the above description. Again, since that there is more than one possible consideration approach, we prefer using the term auxiliary-problem-paradigm rather than auxiliary-problem. We note, that by referring to the feasible-set, we mean that some constraints could be given on the use (for evaluation) of certain members of the candidate-sets, hence only feasible members should be included in the evaluation-set.

The proposed paradigm spans many possible well-defined problems that can be presented both in terms of crisp and fuzzy sets and relations. The above descriptions, of the main and auxiliary problem paradigms, use the terms sets and relations. Clearly, as such the paradigm is not restricted to crisp sets and relations. The suggested paradigm assumes hybrid representations by way of conceptual and particular solutions. Commonly, the models for particular solutions in concept-based planning are curves. In contrast, the conceptual solutions are symbolic. The reasoning process is also hybrid in the sense that the consequence (optimal concepts) depends on the mixture of the auxiliary and main problem.

The paradigm might be viewed as an "ill-defined problem," but this seems to be in accordance with the nature of design and planning as discussed in section 3. An

important aspect of the paradigm is that it spans a kind of hybrid MOPs. In the context of Pareto-optimality, it includes the three major strategies used in the concept-based approach (see [9]). In fact, the suggested paradigm extends the scope of concept-based problems from those based on the regular meaning of Pareto-optimality, by leaving the criteria to be used as an open question. Hence it includes concept-based problems, which might be based, for example, on non-Pareto multi-objective optimization criteria such as the weighted sum approach. In itself the paradigm does not provide a proven learning tool but just a suggested tool, which could be used with complementary tools to test the proposal of this paper. Further discussion on the proposed paradigm, as related to learning, is given in the following.

V. DISCUSSION

Given the practice from engineering design, as described in section 3, it seems that evaluating concepts is a major obstacle, and a subjective matter. Engineers evaluate concepts for a particular design task based on their past experience and on their understanding of the concept and the task. Eventually engineers reduce the search space by selection of a preferred concept. In self-learning to conceptually plan, the learner should be able to imagine different experiences with conceptual solutions. The proposed paradigm allows associating a concept with different problems within one learner. The wide scope of the paradigm should be viewed in light of the citation, in section 3, from [4]. It should also be viewed in light of engineering design, where iterative problem setting is a common practice even for the experienced engineers. The proposed paradigm provides the room for such iterations. With this respect it should be acknowledged that the paradigm is not essential for defining different problems! By changing the environment, and or the start and goal points, a different planning problem can easily be defined. So what is new in terms of imagining various problems? We claim that the paradigm provides a mechanism to create various planning problems even within the same environment and start and goal (but not just). This is due to the possibility to re-examine the environment from different and subjective viewpoints concerning the values of the conceptual plans and the way they are compared in the multi-objective space. The use of different problem definitions, to compare the concepts, amounts to imagining various situations that are not included in the learnt model of the environment.

From a multi-competence cybernetics viewpoint, we may ask is the paradigm bio-inspired? Or, in deferent terms, is it of relevance to the understanding of nature? Our conviction

is that the answer to the later part is positive. We therefore assume that the proposed paradigm should prove helpful for the development of cognitive systems. Some of our initial ideas, with this respect, are discussed below in the context of self-learning to plan. Consider the proposed paradigm as a mechanism to support imaginative testing and re-testing of concepts, under different problems and evaluation rationale. Then selectively memorize "optimal" concepts. To understand this vague idea, assume an analogy between concepts and species [7], as well as an analogy between "niches over history" and "re-testing by imagination." Species that have survived certain niches may have failed to survive niche changes over time. We search for species that over history of many niches (many evaluation problems) survived.

It is important to examine the paradigm in the light of constructivism-based Darwinian learner and soft computing. As discussed in the introduction, hybrid bio-inspired systems can be built using soft computing methods. FL might prove to be most valuable in modeling concepts and relations within a subjective framework of self-learning. As discussed in section 3, in the interactive scheme, of the concept-based approach, humans provide much of the modeling, and the computer role is to run the optimization process based on the provided models. For the development of the foreseen multi-competence Darwinian knowledge acquisition systems, modeling methods should be discussed. As pointed out in the introduction, low level perception and learning of the environment are not within the scope of this paper. Hence we are bound to assume the availability of a certain model of the environment. We assume, as hinted in the introduction, that prior to self-learning to plan, the robot experience an initial stage of knowledge acquisition from a teacher. Following that stage, it is assumed that the robot can use the paradigm and imagine various situations and problems. At this stage the robot can use any of the methods discussed in the literature on the concept-based approach, e.g., [9], or similar ones, to find C^* .

The resulted optimal concepts can be understood as robust in a sense which depends on the examined problem. In fact for any well-defined auxiliary and main problem, the robot can create a set C^* and memorize it for future use. It can also operate on the various optimal sets, which have been achieved from different problems to create a final set to be memorized (e.g., by memorizing the most frequent concepts). In summary, the problem paradigm of section 4 spans infinite alternatives to define a problem for self-learning to plan. It should be considered as its strength, in view of the discussion of section 3.

To manage the current discussion, the exposition has been restricted to full plans, and the use of state-based planning. Conceivably the extension to include sub-plans is achievable. With this respect it is noted that in the context

of self-learning to plan, it would be possible to consider the start and goal states within additional objectives in the multi-criteria space. This might support the creation and evaluation of conceptual sub-plans. Similarly, it is believable that the proposed methodology can be extended from state-based planning to action-based planning. Finally, an interesting issue, to be explored in the future, is the representation of the paradigm in a meaningful code that will provide, when evolved, meaningful learning results.

VI. SUMMARY AND CONCLUSIONS

In this paper we propose the notion of a constructivism-based learner that is concerned with conceptual planning. It is a system with an internal self-learning process, which transforms internal representations into useful knowledge based on the exploration of useful problems, particular solutions, and conceptual solutions. Inherent to the presented problem paradigm is a unique hybrid knowledge representation and reasoning, which is required in the evaluation of conceptual plans based on particular plans. The discussion involves a proposed problem and solution paradigm. The suggested paradigm provides a mean to reformulate problems with respect to multi-criteria evaluation of concepts. The study includes detailed explanations on the rationale for the proposed learning methodology based especially on constructivism learning theory, and on observations concerning conceptual design by engineers. It is concluded that the proposed paradigm should support self-learning by robots to conceptually plan.

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