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基于知识的智能优化引导方法研究进展

邢立宁 [1]　　陈英武 [1]

摘　要　为了提高智能优化方法的优化性能, 国内外学者通过知识来加强对优化过程的引导. 对基于知识的智能优化引导方法进行了综述: 一方面通过传统人工智能手段来实现对智能优化方法的引导; 另一方面通过特定知识模型来实现对智能优化方法的引导. 从前期优化过程中挖掘有用知识, 采用知识来引导后续优化过程, 极大地提高了智能优化方法的优化性能.

关键词　人工智能, 智能优化算法, 引导, 全局收敛, 遗传算法, 知识模型

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Research Progress on Intelligent Optimization Guidance Approaches Using Knowledge

XING Li-Ning[1]　　CHEN Ying-Wu[1]

Abstract　To improve the performance of intelligent optimization approaches, many researchers have used knowledge to strengthen the optimization process guidance. The intelligent optimization guidance using knowledge is reviewed in this work. The intelligent optimization guidance is normally executed via artificial intelligence approaches and special knowledge models. Also, some researchers have proposed algorithms which have a double layer evolution mechanism. These improved approaches can discover some knowledge from the previous iterations, then use the discoverd knowledge to guide the subsequent iterations.

Key words　Artificial intelligence, intelligent optimization approaches, guidance, global convergence, genetic algorithm, knowledge model

智能优化方法是当前研究的热点问题, 其缺点是容易出现早熟收敛和收敛速度较慢. 导致这些缺点的重要原因就是智能优化方法中缺乏明确的导向因子. 国内外学者一方面通过传统人工智能手段来实现对智能优化方法的引导, 另一方面通过特定知识模型来实现对智能优化方法的引导.

1　采用传统人工智能手段进行引导

采用传统人工智能手段对智能优化算法进行引导, 如采用禁忌搜索[1]、文化算法[2] 和采用机器学习[3] 来控制进化等[4]. 在具体实施时, 必须首先抽取一些进化过程中尽可能一般和重要的规则, 利用禁忌搜索、文化算法和机器学习等算法进行学习, 然后根据学习得到的规则控制个体进化.

为了平衡进化过程中选择操作正向作用和交叉 (变异) 操作的破坏性影响, 范磊等[5] 采用归纳学习方法来引导进化过程: 采用归纳学习方法从进化历史进程中抽取出能反映过去进化的错误和成功的规则, 进而用它们来引导后续进化过程, 保证在避免重复错误的同时加速进化. 基于函数优化和布局求解的实验验证了其有效性.

曹先彬等[6] 借鉴个体进化的生命周期性, 提出了一种基于生命期引导的生态进化模型. 基于此模型的算法在个体生命期的各个阶段设置了相应的引导算子, 使个体在整个生命期都基于其生态特征而被引导进化. 实验结果验证了其优越性.

为了提高粒子群算法中粒子搜索全局最优解的准确度, 岑宇森等[7] 提出了基于知识空间的分组式粒子群算法. 该算法使用 K-means 算法对粒子群进行分组, 利用较小的最大飞行速度加强粒子在组内的局部搜索能力, 并将 “知识空间” 的概念带入到分组中, 由知识空间中的粒子来引导群中粒子前往更好的解空间搜索.

李亚男等[8] 在遗传算法中采用专家知识辅助寻优, 并将该改进遗传算法应用到无功规划优化中. 依据专家知识对少数被选中的个体动态形成本厂、站的就地无功/电压控制的有效变量集进行人工调整, 可改善遗传算法的局部寻优能力. 对某实际系统的计算表明, 结合专家知识的遗传算法能够更有效地找到全局最优.

柴啸龙[9] 将领域知识通过禁忌连接集的形式加入蚁群规划算法中, 相邻动作层的很多互斥信息通

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1. 国防科学技术大学信息系统与管理学院管理系　长沙 410073
1. Department of Management, College of Information System and Management, National University of Defense Technology, Changsha 410073

过禁忌连接集只需计算一次, 不带入主循环计算中, 可以较好地提升算法的执行效率, 实例分析表明这一策略是有效的.

基于传统人工智能手段对智能优化方法进行引导的缺陷在于很难找到尽可能一般和重要的规则, 而且这些规则缺乏全局性, 没有考虑到随着个体的进化, 个体所处的环境也在不断变化, 因而相应的规则也应该变化[4].

2 基于特定知识模型的引导法

采用特定知识模型对智能优化算法进行引导时, 在智能优化算法运行之初就已确定了知识的基本形式, 相关知识按照固定规则随着算法演化而不断调整, 然后, 采用已获得知识来指导后续个体的进化. 采用特定知识模型对智能优化算法进行引导也可理解为演化与学习之间的交互 (Interaction between evolution and learning)[10−15]. 大量研究表明: 演化与学习之间的交互能极大提高智能优化方法的性能[16]. 国内外学者分别采用版本空间[17]、基于案例的存储器[18]、Q-学习系统[19−20] 和 AQ-学习系统[21] 等多种途径来实现演化与学习之间的交互.

2.1 基于存储器的引导法

很多学者尝试采用存储器来实现演化与学习之间的交互. Chung 等[22] 将个体优良特征定义为信念 (Beliefs), 将获得的信念保存在存储器中, 采用信念来不断改进后续个体. Branke[23] 将一些较优个体保存在存储器中, 采用已获得的较优个体来改进后续个体.

Gantovnik 等[24−25] 采用存储器在遗传算法中实现演化与学习之间的交互, 并使用这种改进遗传算法来解决混合变量优化设计问题. Louis 等[26] 采用带有存储器的遗传算法来求解旅行商问题. Yang[27−28] 采用基于存储器的移民方式在遗传算法中实现演化和学习之间的交互, 并使用这种改进遗传算法求解动态优化问题.

苏淼等[29] 采用免疫记忆方式在蚁群算法中实现演化与学习之间的交互, 并使用这种改进蚁群算法来求解武器目标分配问题. Acan[30] 使用外部存储器 (External memory) 在蚁群算法中实现演化与学习之间的交互. 在此基础上, Acan[31] 在外部存储器中加入了局部置换 (Partial permutations) 功能, 进一步提高了改进蚁群算法的效率. Shamsipur 等[32] 使用外部存储器在蚁群算法中实现演化与学习之间的交互.

2.2 基于案例的引导法

很多学者使用案例来实现演化与学习之间的交互[33−34]. Louis 等[18] 使用案例推理方法从案例存储器中选择较优特征来改进后续个体. Louis 等[33] 在遗传算法中采用案例注入方式来实现演化与学习之间的交互, 并使用这种改进遗传算法来求解旅行商问题. Rasheed 等[34] 采用案例学习方式在遗传算法中实现演化与学习之间的交互. Babbar-Sebens 等[35] 提出了一种基于案例的宏观交互式遗传算法 (Case-based micro interactive genetic algorithm), 主要通过案例存储器和案例推理来实现演化与学习之间的交互.

2.3 基于学习演化模型的引导法

学习演化模型 (Learnable evolution model) 主要采用机器学习方法来指导演化进程. Coletti[36] 对学习演化模型进行了初步研究, Wojtusiak[37] 研究了学习演化模型中的约束优化问题, Kaufman 等[38] 采用学习演化模型来解决热交换器设计问题, Jourdan 等[39] 使用学习演化模型来解决多目标水系统设计问题, Domanski 等[40] 采用学习演化模型来求解优化设计问题. 目前, 学习演化模型的最新版本为 LEM3. Wojtusiak 等[41] 应用 LEM3 来解决复杂函数优化问题.

近年来, 越来越多的学者开始使用学习演化模型在智能优化方法中实现演化与学习之间的交互[16, 21]. Michalski 等[42] 在总结学习演化模型最新进展的基础上, 在智能优化方法中采用演化学习模型来实现演化与学习之间的交互[43]. 在 Michalski[21] 构建的学习演化模型中, 主要采用机器学习方法来实现演化与学习之间的交互. Ho 等[16] 采用学习型遗传框架 (Learnable genetic architecture, LEGA) 来实现演化与学习之间的交互. Wojtusiak[44] 设计了一种可用于多种智能优化方法的 LEM3 系统.

2.4 基于神经网络的引导法

针对遗传算法个体进化缺乏明确导向的缺点, 顾慧等[4] 提出了一种基于知识模型的改进遗传算法: 利用神经网络的学习功能, 从当前两代个体的信息中获取一定知识, 用于控制下一代某些个体的进化. 该算法既保留了遗传操作算子, 同时利用神经网络构造相应的知识模型, 用于引导个体进化, 使得改进遗传算法既保留了遗传算法强大的全局随机搜索能力, 又具有神经网络的自学习能力和强鲁棒性.

采用知识模型对智能优化方法引导时, 现有研究还仅限于针对特定问题采用特定模型加强对特定方法的引导, 研究成果缺乏系统性、通用性和可扩展性, 还没有将其作为一个方法体系进行研究.

2.5 基于知识模型的引导法

在现有智能优化方法的基础上, 邢立宁等[45] 设计并实现了多种知识型智能优化方法. 该方法采用智能优化模型和知识模型相结合的集成建模思路: 智能优化模型按照 "邻域搜索" 策略对待优化问题的可行空间进行搜索; 知识模型从前期优化过程中挖掘有用知识, 然后, 采用知识来指导智能优化模型的后续优化过程. 将智能优化模型和知识模型有效地结合起来, 极大地提高了知识型智能优化方法的优化绩效. 采用知识型智能优化方法求解函数优化问题[46]、非对称旅行商问题[47]、双层 CARP (Capacitated arc routing problem) 优化问题[48−49] 及柔性作业车间调度问题等经典问题[50−54], 均取得了比较满意的结果.

3 结束语

本文对基于知识的智能优化引导方法进行了综述: 一方面通过传统人工智能手段来实现对智能优化方法的引导; 另一方面通过特定知识模型来实现对智能优化方法的引导. 根据笔者的理解, 可通过以下方面的研究进一步改进基于知识的智能优化引导方法:

1) 扩展知识的种类, 结合实际的工程问题, 设法从优化过程中挖掘能有效提高优化绩效的更多类型的知识; 同时也可将专家对实际问题的经验知识抽象出来, 应用经验知识来有效地指导优化过程, 从而尽可能地提高优化效率.

2) 采用新的知识挖掘方式. 可考虑采用机器学习或数据挖掘等先进的知识挖掘方式从优化过程中发现有用知识. 采用机器学习或数据挖掘等方式从优化过程中挖掘知识, 一方面可能会高效地挖掘出一些非常有用的知识; 另一方面可能会极大地增加优化过程中的计算负担. 这两者之间的权衡也需要通过进一步的研究和实验来解决.

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邢立宁　国防科学技术大学信息系统与管理学院讲师. 主要研究方向为智能优化方法, 管理理论与管理决策技术. 本文通信作者.
E-mail: xinglining@gmail.com
(**XING Li-Ning**　Lecturer at the College of Information System and Management, National University of Defense Technology. His research interest covers intelligent optimization methods, management theory, and management decision technology. Corresponding author of this paper.)

陈英武　国防科学技术大学信息系统与管理学院教授. 主要研究方向为管理理论与管理决策技术.
E-mail: ywchen@nudt.edu.cn
(**CHEN Ying-Wu**　Professor at the College of Information System and Management, National University of Defense Technology. His research interest covers management theory and management decision technology.)