Part I Evolutionary Computation

Chapter 5
Evolutionary Programming

Evolutionary Programming

- **5-1 Basic EP**
- **5-2 Implementation of EP**
- **5-3** 进化算法对比

Evolutionary Programming

- **1962, L.J.Fogel**
- **Using simulated evolution to develop artifical intelligence.**
- **Emphasizes the development of behavioral models and not genetic models.**
- **Consider phenotypic evolution.**
- **Two evolutionary operators, namely variation through application of mutation operators, and selection.**

5-1 Basic EP

- **Intelligence can be viewed as "that property which allows a system to adapt its behavior to meet desired goals in a range of environments." A model has been developed to imitates evolution of behavioral traits.**

$$\chi(t) = (\mathbf{x}(t), \sigma(t))$$

Main components

- **Initialization**: a population of individuals is initialized to uniformly cover the domain of the optimization problem.
- **Mutation**: introduce variation in the population to produce new candidate solutions. Each parents produces one or more offspring through application of the mutation opertor.

main components

- Evaluation: a fitness function is used to quantify the “behavioral error” of individuals.
- Selection: select those individual that survive to next generation.

Algorithm

Set the generation counter, $t = 0$;
Initialize the strategy parameters;
Create and initialize the population, $\mathcal{C}(0)$, of n_s individuals;
for *each individual*, $\mathbf{x}_i(t) \in \mathcal{C}(t)$ **do**
    Evaluate the fitness, $f(\mathbf{x}_i(t))$;
end
while *stopping condition(s) not true* **do**
    for *each individual*, $\mathbf{x}_i(t) \in \mathcal{C}(t)$ **do**
        Create an offspring, $\mathbf{x}_i^{'}(t)$, by applying the mutation operator;
        Evaluate the fitness, $f(\mathbf{x}_i^{'}(t))$;
        Add $\mathbf{x}_i^{'}(t)$ to the set of offspring, $\mathcal{C}^{'}(t)$;
    end
    Select the new population, $\mathcal{C}(t+1)$, from $\mathcal{C}(t) \cup \mathcal{C}^{'}(t)$, by applying a selection operator;
    $t = t + 1$;
end

Comparison

- EP emphasizes phenotypic evolution instead of genotypic evolution. The focus is on behaviors.
- Do not make use of any recombination operator.
- Use a relative fitness function to quantify performance with respect to a randomly chosen group of individuals.
- Selection is based on competition. Those individuals that perform best against a group of competitors have a higher probability of being included in the generation.

Comparison

- Parents and offspring compete for survial.
- The behavior of individuals is influenced by strategy parameters, which determine the amount of variation between parents and offspring.

5-2 Implementation

- **1. Representation**
- 实数向量编码

$$(\mathrm{x},\sigma)=(x_1,x_2,\cdots x_n,\sigma_1,\sigma_2,\cdots\sigma_{n_\sigma})$$

2. Mutation

- Mutation is the only means of introducing variation in an EP population, it is importmant that the design of a mutation operator considers the exploration-exploitation trade-off.
- The variation process should facilitate exploration in the early stages of the search to ensure that as much of the search space is coverd as possible.
- After an initial exploration phase, individuals should be allowed to exploit obtained information about the search space to fine tune solution.

$$x'_{ij}(t) = x_{ij}(t) + \Delta x_{ij}(t)$$

$$\Delta x_{ij}(t) = \Phi(\sigma_{ij}(t))\eta_{ij}(t)$$

where $\Phi : \mathbb{R} \rightarrow \mathbb{R}$ is a function that scales the contribution of the noise, $\eta_{ij}(t)$

1 Non-adaptive EP

- **Non-adaptive EP**: the deviations in step sizes remain static.

$$\Phi(\sigma_{ij}(t)) = \sigma_{ij}(t) = \sigma_{ij}$$

$$x'_{ij}(t) = x_{ij}(t) + N_{ij}(0, \sigma_{ij})$$

- The disadvantage of this approach is that a too small value for σ limit exploration and slows down convergence. Otherwise a too large value limits exploitation and the ability to fine-tune a solution.

2 Dynamic EP

- Dynamic EP: the deviations in step sizes change over time using some deterministic function, usually a function of the fitness of individuals.
- The first approaches to change the values of strategy parameters over time was to set them to the fitness of the individual.

$$\sigma_{ij}(t) = \sigma_i(t) = \gamma f(\mathbf{x}_i(t)) \qquad \gamma \in (0, 1].$$

$$\begin{aligned} x'_{ij}(t) &= x_{ij}(t) + N(0, \sigma_i(t)) \\ &= x_{ij}(t) + \sigma_i(t) N(0, 1) \end{aligned}$$

The phenotypic distance from the best individual can be used. y^ is the most fit individual.

$$\sigma_{ij}(t) = \sigma_i(t) = |f(\hat{\mathbf{y}}) - f(\mathbf{x}_i)|$$

Advantage

- The weaker an individual is, the more that individual will be mutated. the offspring then moves far from its weak parent.
- The stronger an individual is, the less the offspring will be removed from its parent, allowing the current good solution to be refined.

Disadvantages

- **If fitness values are very large, step sizes may be too large, causing individuals to overshoot a good minimum.**
- **If knowledge of the optimum is available, using an error measure will be appropriate.**

Other methods

$$x'_{ij}(t) = x_{ij}(t) + \sqrt{\beta_{ij}(t) f(\mathbf{x}_i) + \gamma_{ij}} + N_{ij}(0,1)$$

proportionary constant **offset parameter**

$$x'_{ij}(t) = x_{ij}(t) + \beta_{ij}\sigma_i(t) N_{ij}(0,1)$$

$$\sigma_i(t) = \frac{f(\mathbf{x}_i(t))}{\sum_{l=1}^{n_s} f(\mathbf{x}_l(t))}$$

normalized fitness value

3 Self-adaptive EP

- **Self-adaptive EP**:in which case deviations in step sizes change dynamically.
- Strategy parameters can be "evolved"
- Reference to ES
- **Additive methods**:η is the learning rate.
-

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) + \eta\sigma_{ij}(t)N_{ij}(0,1)$$

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) + \sqrt{f_\sigma(\sigma_{ij}(t))}N_{ij}(0,1)$$

$$f_\sigma(a) = \begin{cases} a & \text{if } a > 0 \\ \gamma & \text{if } a \leq 0 \end{cases}$$

- **Multiplicative methods**
- $$\sigma_{ij}(t+1) = \sigma(0)(\lambda_1 e^{-\lambda_2 \frac{t}{n_t}} + \lambda_3)$$

- **Lognormal methods**

$$\sigma_{ij}(t+1) = \sigma_{ij}(t)e^{(\tau N_i(0,1)+\tau' N_{ij}(0,1))}$$

$$\begin{aligned} \tau' &= \frac{1}{\sqrt{2\sqrt{n_x}}} \\ \tau &= \frac{1}{\sqrt{2n_x}} \end{aligned}$$

3. Selection

- **the new population is selected from all the parents and their offspring.**
- **随机型p竞争法**
- **1）从μ个父代和μ个子代中，依次选出一个个体i**
- **2）从2μ个个体中，随机选择p个个体**
- **3）比较个体i与p个个体适应度的优劣，记录个体i的适应度优于或者等于p个体的次数，作为i的得分Wi**
- **4）依次评价完2μ个个体。**
- **5）对W进行排序，选出前μ个个体作为下一代。**

- **p**是随机选择，优良个体进入下一代的机会会大些，但是也有较差个体会进入。
- 建议**p=0.9μ**

总结——进化算法比较

	GA	ES	EP
重点强调	染色体操作	个体行为变化	种群行为变化
个体编码	离散	连续	连续
适应度函数	变换目标函数	直接使用目标函数	变换目标函数
交叉算子	主要搜索方法	辅助搜索方法	无
变异算子	辅助搜索方法	主要搜索方法	唯一搜索
选择算子	概率的	确定的	概率的