Evolving PSO Algorithm Design in Vector Fields Using Geometric Semantic GP

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ABSTRACT

This paper investigates the possibility of evolving new particle swarm equations representing a collective search mechanism, acting in environments with unknown external dynamics, using Geometric Semantic Genetic Programming (GSGP). The proposed method uses a novel initialization technique – the Evolutionary Demes Despeciation Algorithm (EDDA)– which allows to generate solutions of smaller size than using the traditional ramped half-and-half algorithm. We show that EDDA, using a mixture of both GP and GSGP mutation operators, allows us to evolve new search mechanisms with good generalization ability.

CCS CONCEPTS

• **Theory of computation → Design and analysis of algorithms**; *Bio-inspired optimization*;

KEYWORDS

Semantics, Genetic Programming, Geometric Semantic Mutation, EDDA, Particle Swarm Optimization, Vector Fields

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Introduction. In the last few years, one of the most significant developments in GP research is the integration of semantic awareness in the evolutionary process. One particular type of Semantic GP is Geometric Semantic GP (GSGP) [3], which explores directly the semantic space and whose operators may be more effective than the traditional ones, due to the fact that they induce a unimodal fitness landscape for any supervised learning problem. However, being widely used to solve symbolic regression problems, there is still no research in the literature on using GSGP for evolving search algorithms. The main goal of this study is to cover this gap and to investigate whether GSGP can be used to evolve new successful stochastic population-based algorithms (such as PSO [1]). At the same time, previous studies (see for instance [2]) dedicated to the Extended Particle Swarms (XPSO) project, indicate that GP can automatically generate new PSO algorithms that outperform standard handmade PSOs. In this paper, we address the Vector Field PSO (VF-PSO) algorithm introduced in [1], as a variation of PSO under the influence of external unknown dynamics, modeled by vector fields. More specifically, we focus on the possibility of the evolution of new velocity VF-PSO equations (VFPS), to make this algorithm more robust to external influence. We look after this issue by adapting a recently introduced initialization algorithm, called EDDA [4], which uses both GP and GSGP mutation operators. The results show that the mixture of different mutation operators leads to a better evolution of VFPS individuals in terms of generalization ability (due to GSGP mutation, i.e. GSM) and size (due to standard GP mutation).

Vector Field PSO. VF-PSO is designed as a collective search mechanism for aerial micro-robots based on PSO in environments with unknown external dynamics modeled by vector fields [1]. A vector field (denoted as VF) is represented as a two-dimensional uniform grid G of vectors over the search space S, which influence the motion of particles in the following way:

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{v}_i(t+1) + \sum_{k=0}^{K} \vec{V}F(\mathbf{g}^k) \tag{1}$$

$$\vec{v}_i(t+1) = w\vec{v}_i(t) + c_1\vec{\phi}_1(\vec{x}^{pbest}(t) - \vec{x}^i(t)) + \\ + c_2\vec{\phi}_2(\vec{x}^g(t) - \vec{x}^i(t)) \tag{2}$$

where $\vec{V}F(\mathbf{g}^k)$ is the constant vector field value at the corresponding cell $\mathbf{g}^k$ of the grid G. The values of VF are constant only within the considered cell, but differ among the cells themselves. K is the number of cells in the grid G, which the particle i crosses (intersects) along the movement from its position at time t, i.e. $\vec{x}_i(t)$, to the position at $t+1$, i.e. $\vec{x}_i(t+1)$. $\mathbf{g}^0$ indicates the cell with initial position of the particle $\vec{x}_i(t)$ at time t and $\mathbf{g}^K$ the cell with final position $\vec{x}_i(t+1)$ at $t+1$. All the other $\mathbf{g}^k$ indicate the cells of the grid G, which are in between of $\mathbf{g}^0$ and $\mathbf{g}^K$ for the corresponding particle i. $\vec{\phi}_1$ and $\vec{\phi}_2$ are two random vectors with values uniformly distributed in $[0, 1]$ in each dimension, c_1 and c_2 are two positive

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constants called acceleration coefficients, which determine the relative influence of the personal and social experiences. The movement described by Equation 1 and Equation 2 is denoted as Vector Field PSO (VF-PSO).

Evolutionary Demes Despeciation Algorithm. Evolutionary Demes Despeciation Algorithm (EDDA) [4] is an initialization technique that can be used for both GP and GSGP, inspired by the biological concepts of demes evolution and despeciation. Demes despeciation is a natural phenomenon, which indicates the combination of demes (local populations) of previously distinct species in new populations. According to this, in EDDA a population of N individuals is initialized using the best individuals found in N different demes that have been run independently for few generations under distinct evolutionary conditions. Following [4], in this work one part of these demes is evolved via standard GP, while the remaining part using GSGP. Thus, EDDA produces an initial population of individuals which genetic lineage is determined by two different algorithms, i.e. GP and GSGP.

Semantics for VFPS evolution. In our system, GP individuals p_i are performed by the Equation 2. Our terminal set is: $\mathcal{T} = \{\vec{x}_i, \vec{v}_i, \vec{x}_i^{pbest}, \vec{x}^g, \vec{x^c}, \sigma_x, C, \vec{R}(0,1)\}$, where σ_x is the average distance of each particle $\vec{x}_i$ to the center of mass $\vec{x^c}$. As a function set, we have used: $\mathcal{F} = \{+, -, *, sin\lessdot, cos\lessdot, \langle\cdot,\cdot\rangle, \times, LF\}$, where $\langle\cdot,\cdot\rangle$ and $\times$ are the dot and cross product of two vectors correspondingly, LF is a logistic function applied to each vector component. As fitness cases FC we consider the class of optimization problems, which is performed by certain objective function $h(\vec{x}) : \mathbb{R}^n \to \mathbb{R}$, but with different global optimal solutions $\{\vec{c}_j\}_{j=1}^d \in \mathbb{R}^n$. The vector of the respective expected output (target) $\vec{t} \in \mathbb{R}^d$ consists of function values at the corresponding global optima $\{\vec{c}_j\}_{j=1}^d$ of the considered problem class defined by FC and represents a target point in the semantic space $\mathcal{S}$. The results of $p_i(\vec{c}_j)$ evaluations inside the VF-PSO are performed as the fitness values of the global best particles position x_j^g in the swarm, i.e. $p_i(\vec{c}_j) := h(\vec{x}_j^g - \vec{c}_j)$, for each $j \in \{1..d\}$. To minimize the effects of random factors, while executing p_i inside the VF-PSO on the considered problem class FC, each p_i is run for r times on each of $\vec{c}_j$ instances with fixed initial population for all $\{\vec{c}_j\}_{j=1}^d$ within the single run $l \in \{1..r\}$. Thus, the semantics $\vec{s}_{p_i}$ of an individual p_i on a problem class FC is a point in the semantic space $\mathcal{S}$ represented by the average fitness values of r global best positions of VF-PSO, obtained by each $p_i(\vec{c}_j)$ within r runs for each of the corresponding $\vec{c}_j$ problems. The fitness function $f : \mathcal{S} \to \mathbb{R}_{\geq 0}$ is represented as average of the differences between expected and obtained results executed on all problem instances of the corresponding problem class FC.

Experiments. In order to investigate the advantage of using EDDA (i.e. of having mixed genetic operators) for the evolution of VFPS equations, we simulate the mixture of GP and GSGP mutations performed as: MIX-25%, MIX-50% and MIX-75%, where "MIX-m%" represents an evolutionary process where both GSM and standard GP mutation are applied to the same population, with respectively m% and $(100 - m)$% probabilities (as in [4], while using EDDA to initialize the population). To validate the introduced configurations, we compare them with systems that use pure (i.e. 100%) GSGP and standard GP mutation operators. Due to page limitations, we report the experiments without going into details about parameter settings.

Results and Discussion. It is expected that the mixture of different mutation operators will lead to a better evolution of VFPS individuals in terms of generalization ability (due to GSM) and size (due to standard GP mutation). Experimental results show that in the case of no vector fields (standard PSO), the MIX systems obtained results that are intermediate between the ones obtained by standard GP and the ones obtained by GSGP, and never worse than the best of the two. However, the situation looks different when vector fields are employed. In this case, standard GP outperformed all the other systems, while GSGP was consistently outperformed by all the other systems. Concerning the MIX systems, also when vector fields are employed, their performance is, in most of the cases, intermediate between the one of standard GP and the one of GSGP. Figure 1 reports the results obtained on the most difficult fitness case (according to [1]) and shows the evolution of the median best fitness of the evolving individuals over generations.

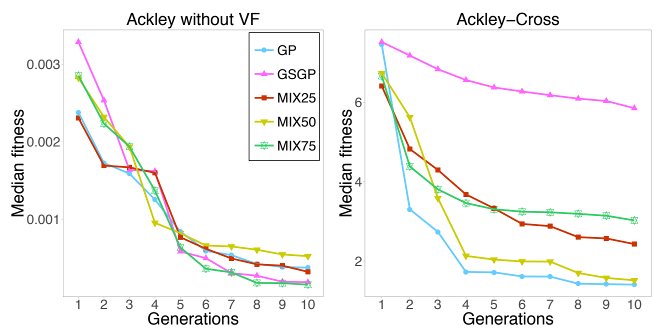

Figure 1: Comparison between different mixtures of GSM and traditional genetic operators.

Conclusion. Using GSGP alone for evolving new VFPS is not as efficient as using GP. Besides, we are interested in "small" individuals, i.e. with similar structure and size as standard PSO force equation, what is anyway impossible to achieve by GSGP as the size of its evolved individuals grows from generation to generation. On the other hand, the study has shown that the mixture of mutation operators can be beneficial and seems to inherit the best features of both GSM and standard GP mutation, what allows us to produce high-quality individuals with good generalization ability and smaller size.

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