Multi-swarm Genetic Gray Wolf Optimizer with Embedded Autoencoders for High-dimensional Expensive Problems

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Abstract

- High-dimensional expensive problems are often encountered in the design and optimization of complex robotic and automated systems, and they suffer from a time-consuming fitness evaluation process. It is extremely challenging and difficult to produce promising solutions in high-dimensional search space
- This work proposes an evolutionary optimization framework with embedded autoencoders that effectively solve optimization problems with high-dimensional search space
- Multiple subpopulations coevolve iteratively in a distributed manner. One subpopulation is embedded by an autoencoder, and the other one is guided by a newly proposed Multi-swarm Gray-wolf-optimizer based on Genetic-learning (MGG)
- The proposed multi-swarm framework is named Autoencoder-based MGG (AMGG)
- AMGG consists of three proposed strategies that balance exploration and exploitation abilities
- AMGG is compared with several widely used algorithms by solving benchmark problems and a real-life optimization one
- The results well verify that AMGG outperforms its peers in terms of search accuracy and convergence efficiency

Introduction

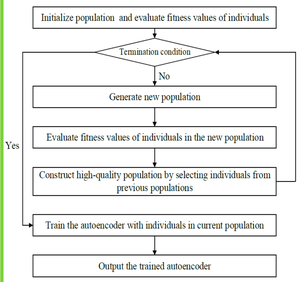
- Evolutionary algorithms (EAs) are inspired by the evolutionary operations of living organisms in nature. EAs have been widely applied in robotics and automation, industrial scheduling, resource allocation
- With the advent of cloud computing, big data, and artificial intelligence, more optimization problems suffer from high-dimensional expensive problems. Moreover, increasing landscape complexity brought by high dimension makes traditional EAs difficult to jump out of local optima
- Autoencoders for dimension reduction have attracted extensive attention because they possess a reconstruction phase

Goal: Effectively solve optimization problems with high-dimensional search spaces

- Novel evolutionary optimization framework with embedded autoencoders named Autoencoder-based Multi-swarm Gray-wolf-optimizer based on Genetic-learning (AMGG)
- Multiple subpopulations coevolve iteratively in a distributed manner
  - One subpopulation is embedded by an autoencoder
  - The other one is guided by a newly proposed Multi-swarm Gray-wolf-optimizer based on Genetic-learning (MGG)
- Three proposed strategies that balance exploration and exploitation abilities
  - Dynamic-subpopulation Number Strategy (DNS) for reducing the number of subpopulations
  - Subpopulation Reorganization Strategy (SRS) for sharing useful information about each subpopulation
  - Purposeful Detection Strategy (PDS) for escaping from local optima and improving exploration ability

Methodology

- Training process of the autoencoder in stage 1



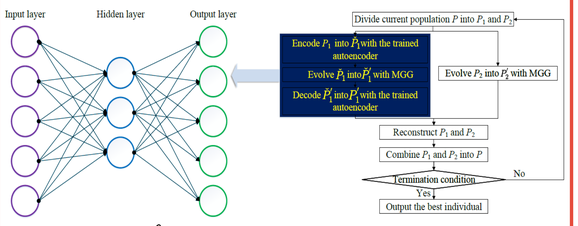
Training flow chart

Algorithm 1 Training of the Autoencoder

```
Initialize ℙ
Initialize d, a, A and C
Evaluate the fitness value f(x_i) of each x_i in ℙ
Ω ← ∅
Initialize x_α, x_β and x_δ
g1←1
repeat
    ℙ' ← MGG(ℙ)
    Evaluate the fitness value f(x'_i) of each x'_i in ℙ'
    for each individual i in ℙ do
        if f(x'_i) < f(x_i) then
            x_i ← x'_i
        end if
    end for
    Update ℙ
    Ω ← Ω∪ℙ
    g1←g1+1
until g1 ≤ ĝ1
┐ ← trainAutoencoder(Ω, ĝ1, d)
return ┐
```

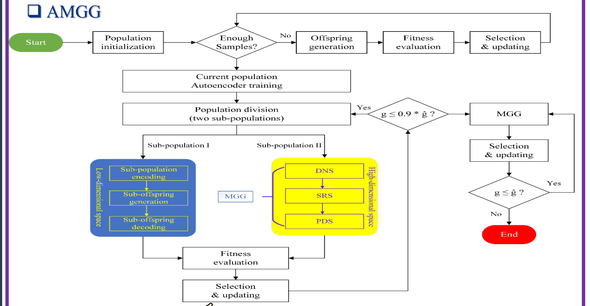
Training pseudo code

- Multi-swarm coevolution in stage 2



Multi-swarm coevolution flow chart

- AMGG



AMGG flow chart

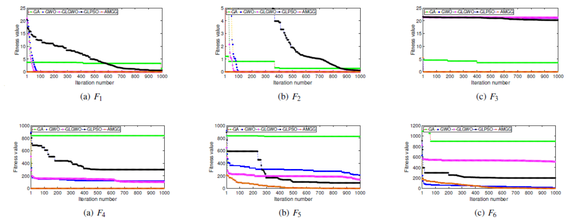
Algorithm 3 AMGG

```
Initialize a, A and C
Evaluate fitness value f(x_i) of each x_i in ℙ
Determine x_α, x_β and x_δ
for g←1 to 0.9*ĝ do
    Perform population splitting
    ℙ1 ← encode(┐, ℙ1)
    ℙ'1 ← MGG(ℙ1)
    ℙ'1 ← decode(┐, ℙ'1)
    Update f(x_i) of each x_i in ℙ'1
    Select the best ||ℙ1|| individuals from ℙ1 and ℙ'1 for constructing ℙ1
    ℙ2 ← MGG(ℙ2)
    Update f(x_i) of each x_i in ℙ'2
    Select the best ||ℙ2|| individuals from ℙ2 and ℙ'2 for constructing ℙ2
    ℙ ← ℙ1 ∪ ℙ2
end for
for g←0.9*ĝ to ĝ do
    ℙ ← MGG(ℙ)
end for
Select x*, from ℙ, and update its fitness value f*
return x*
```

AMGG pseudo code

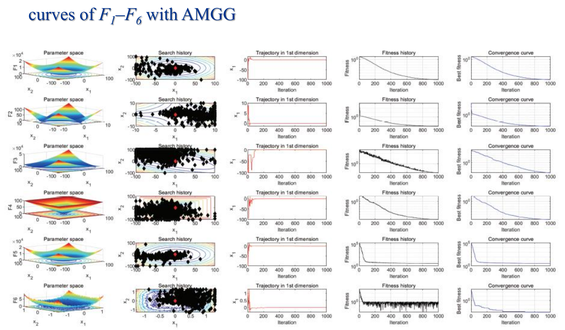
Performance Evaluation

- Fitness values of GA, GWO, GLGWO, GLPSO, and AMGG in each iteration for F_1-F_6

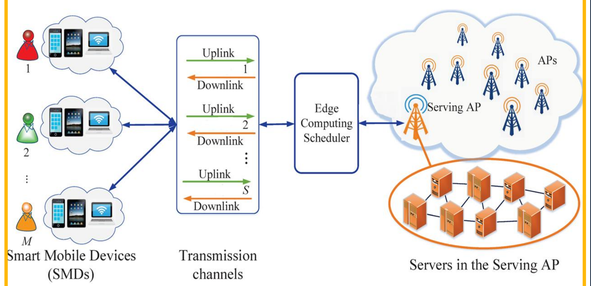


(a) F_1 (b) F_2 (c) F_3 (a) F_4 (b) F_5 (c) F_6

- 2D shapes, search histories, trajectories, fitness histories, and convergence curves of F_1–F_6 with AMGG



- The real-life optimization problem in mobile edge computing systems



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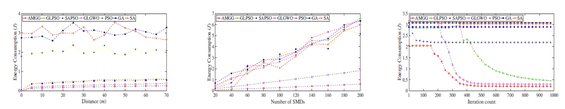


Total energy consumed by all SMDs and edge servers with respect to different distance

Total energy consumed by all SMDs and edge servers with respect to different numbers of SMDs

Evolutionary curves of total energy consumption in each iteration

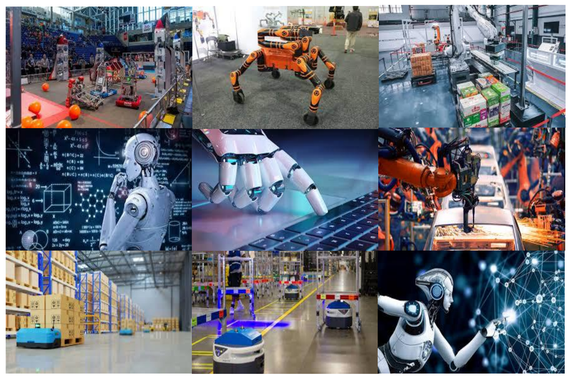
Conclusions and Future Work

Conclusions

- Novel evolutionary optimization framework with embedded autoencoders named Autoencoder-based Multi-swarm Gray-wolf-optimizer based on Genetic-learning (AMGG)
- Superior to other state-of-the-art peers in terms of ability of global exploration, local exploitation, and local optima avoidance

Future Work

- Multi-objective versions for high-dimensional constrained optimization problems
- Parameter tuning and selection by using Taguchi's experimental design method, grid search and other methods
- More real-life optimization problems in other fields



Acknowledgements

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