Adaptive Network Slicing Control Method for Unpredictable Network Variations using Quality-Diversity Algorithms

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Introduction

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Background

- The spread of various internet services
  - Growing need to provide a flexible network
- Network slicing
  - Construction multiple virtual networks (VNs) on a substrate network (SN)
- Virtual Networking Embedding (VNE)
  - The resource allocation problem to determine the mapping between elements of SN and VNs

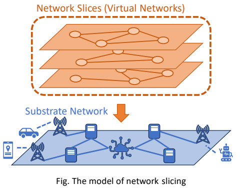

Fig. The model of network slicing

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Problems

- VNE problem is NP-hard
  - It is difficult to derive the optimal solution in the modern huge network
  - Many heuristics have been proposed
- Dynamic environment in practical use
  - Changes of network condition, user request, …
- Need to solve VNE adaptively
  - To derive a feasible solution after such changes utilizing previous solutions

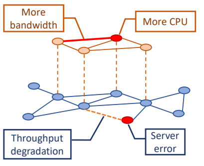

Fig. Changes of VNE environment

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Purpose and method

- Solving VNE adaptively to environmental change
  - Utilizing the previous solutions to develop a new solution immediately
- Genetic algorithm (GA)
  - Based on a model of organism evolution
  - Conventional GAs tend to decrease diversity
- Quality-Diversity (QD) algorithm
  - The methods proposed to generate diverse and superior solutions
  - We focused on one of them, MAP-Elites

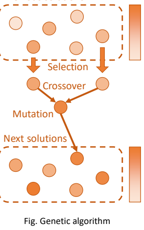

Fig. Genetic algorithm

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Method

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The formulation of VNE Problem

- SN and VN are modeled as undirected graphs
  - SN: $G_S = (N_S, L_S, R_S^n, R_S^l)$
  - VN: $G_V = (N_V, L_V, R_V^n, R_V^l)$
- A solution of VNE is mapping M
  - $M: (N_V, L_V) \rightarrow (N_S', P_S'),\ N_S' \subset N_S$
  - P_S' is a subset of substrate paths
  - Resource requirements must be satisfied
    - e.g. $R_V^n(n_1^V) < R_S^n(n_4^S)$
  - G_V and (N_S', P_S') must have the same topology

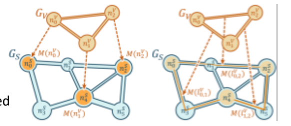

Fig. Example of VNE

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The details of MAP-Elites

- Search for diverse solutions in a feature space
  - The feature space consists of user-designed variables and is divided into cells at a certain granularity
  - Output the best solution within each cell
- The algorithm is below:
  1. Generate an initial population at random
  2. Select an individual from population at random
  3. Mutate a copy of the selected individual
  4. Evaluate fitness and features of a new individual
  5. It compete with the existing individual in the cell (return to 2)

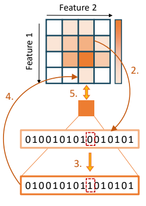

Fig. MAP-Elites algorithm

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The design of feature space

- Important to search for solutions efficiently
  - The dimension of feature space is lower than that of problem space
  - Diverse feasible solutions should be spread in feature space
- Features we designed are below:
  - Feature 1: The total amount of substrate node resources allocated to virtual nodes
  - Feature 2: The total hops of the substrate paths assigned to virtual links
    - We also intend to separate the node and path selections into each feature

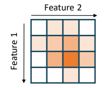

Fig. Feature space

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The encoding of solutions

- Encode a mapping into a genotype
  - Encode the correspondences between elements of SN and VN directly
- Limit the search space
  - To make it possible to encode a mapping with a finite fixed gene length
  - A substrate path is selected from only the k-shortest paths

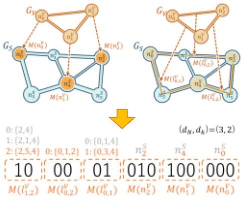

Fig. Encoded solution

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The definition of fitness

- The population evolves so that its fitness becomes higher
  - Define fitness to direct the evolution appropriately
- Fitness: $F(M) = R(M) - \lambda P(M)$
  - $R(M)$: total amount of residual resources
    - Evolve to decrease usage of substrate resources
  - $P(M)$: penalty term
    - The difference between resource requirements and resource allocated actually
    - Evolve to satisfy resource requirements (λ is set adequately large)

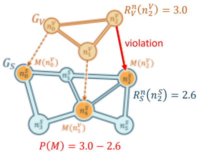

Fig. Resource requirement violation

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Evaluation

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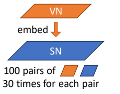
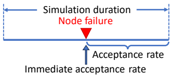
Evaluation method

- We conducted computer simulations of dynamic VNE problem
  - Examine the effect of using QD algorithm
    - Compare MAP-Elites with conventional GAs and another QD algorithm
  - Embed a single VN into a SN in each simulation
    - A specific substrate node failure happens at a certain time
  - Simulations are performed 30 times for 100 different settings



- Compare the means of the metrics below after the environmental change
  - Acceptance rate: the percentage of cases where a feasible solution is found in the duration
  - Immediate acceptance rate: the percentage of cases where a feasible solution exists in the population at the environmental change



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Algorithms used for comparison

- The algorithms we used for comparison are below:
  - Elitism-based GA (EGA)
    - A basic GA that carries over the best individual to the next population for its steady evolution
  - Steady State GA (SSGA)
    - A variant of GA that replaces the worst individual with a new individual in the population
    - Not generating a new population so that there is no generation gap
    - This characteristic is in common with MAP-Elites
  - Novelty Search and Local Competition(NSLC)
    - One of the QD Algorithms
    - Multi-objective optimization for novelty and local competitiveness
    - Novelty: the average Euclidean distance to the k nearest neighbors on the feature space
    - Local competitiveness: the relative fitness in the k nearest neighbors
    - SSGA is used for optimization in this simulation

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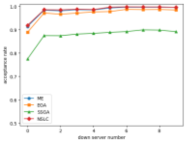
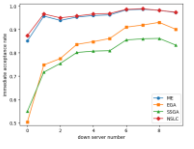
Results

- Acceptance rate
  - No major difference
  - Only SSGA is lower because of the decrease of diversity



- Immediate acceptance rate
  - The QD algorithms are superior to the others
  - No major difference between the two metrics in QD algorithms



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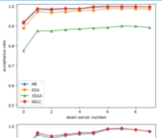
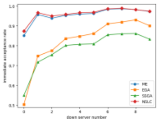
Discussion

- Solution diversity is effective for dynamic VNE
  - The difference of acceptance rates between EGA and QD algorithms is small
  - The diverse and superior solutions found by QD algorithms make possible to adapt for environmental changes more rapidly



- Tolerance of methods using QD algorithms
  - The extent of performance degradation in the case when the substrate nodes with larger resources become unavailable is small in QD algorithms
  - Solutions independent of substrate nodes with larger resources are found in QD algorithms



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Conclusion and future work

- We proposed the method of dynamic VNE using MAP-Elites
  - The mechanism of evolution enables to adapt to environmental changes
- The solution diversity of QD algorithms leads to immediate adaptation
  - The failure tolerance due to finding solutions independent of important nodes
- Future works
  - Better design of feature space to search for solutions more efficiently
  - Developing the method assuming more practical scenario

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