Research Article

Optimization Distribution Method of Computer Sensor Network Communication Based on the Linear Planning Model

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Received 24 November 2021; Accepted 12 February 2022; Published 25 March 2022

In order to explore the optimal allocation method of computer network communication, a linear programming model is proposed. Based on the overall structure of service chain deployment, the integer linear programming model is introduced to make mathematical modeling, so that network resources and load balancing can be effectively utilized under resource and delay constraints. Simulation results showed that in the experiment, 10 to 100 SFC request intensities were generated, respectively, calculating the request acceptance rates of the three deployment algorithms. Under the same conditions, the average request acceptance rate based on the G-kSP algorithm is about 95.4% and about 92.3%, and the greedy deployment algorithm is about 81.7%. We show that the optimized distribution method of computer sensor network communication based on a linear programming model reduces the load balance and time complexity while reducing the request acceptance rate.

1. Introduction

Mobile group intelligence perception uses a large number of mobile devices as the basic perception unit, collects perception data in a large-scale collaborative manner, and realizes the digitization of the physical world. However, with the continuous expansion of the scale of mobile group intelligence perception, the transmission, storage, and processing of massive sensing data are facing new challenges [1]. The emergence of edge computing and end-to-end (Device-to-Device, D2D) communication technologies, for the rapid deployment of perception tasks, perceives the transmission and processing of data and provides a new opportunity. With the help of edge computing, not only can the rapid processing of sensory data be realized at the edge of the network; it can also reduce the occupation of backbone network resources [2]. Therefore, in order to achieve large-scale, high-efficiency, and low-cost mobile group intelligence perception, how to organically integrate edge devices and end devices has become one of the important tasks in the research of mobile group intelligence perception.

With the vigorous development of Internet technology, the text on the web is growing at an exponential rate. Therefore, extracting effective information under a large amount of data improves the efficiency and accuracy of text classification. In improving high-quality and intelligent text classification, the information service that meets the needs of users is of great significance. Feature selection and feature dimensionality reduction are the key steps to achieve feature research. The main research in this article is feature selection technology [3].

For edge computing scenarios, scholars at home and abroad have used edge computing and D2D communication to optimize the execution efficiency of mobile swarm intelligence and reduce implementation costs and energy consumption. Among them, the deployment of edge computing services can speed up the distribution of perception tasks and the collection of perception data; and by using D2D communication technology at the edge of the network, you can build a ubiquitous communication network environment, effectively reducing traditional cellular communication traffic. Due to the large number of participating
devices in group intelligence perception, the application scenarios are changeable; there are still many factors affecting its execution efficiency that need to be discussed and studied in depth [4].

The commonly used method is to reduce the feature dimension of short text and remove redundant and irrelevant features. Zhao et al. proposed a boosted tree classification algorithm; then, a strong classifier is formed; the proposal of this algorithm pushes the text classification algorithm to the peak. Domestic research on text classification methods started late. At present, researchers have studied it from the perspectives of feature selection, weight, classification model, etc. [5]. Research on feature selection mainly focuses on the aspects of feature expansion, feature selection, feature weight calculation, and classification algorithm design. Common feature selection methods are mostly based on common methods, including pattern matching method, word frequency method, chi-square statistics method, and mutual information method [6]. Han et al. analyzed the framework of feature selection methods, from the two perspectives of search strategy and evaluation criteria, analyzed and summarized feature selection methods, analyzed the influencing factors on feature selection, and pointed out the problems to be solved in practical application [7]; He et al. proposed a particle swarm optimization algorithm that adaptively adjusts parameters based on speed information; this algorithm can solve the problem of search failure in complex nonlinear optimization [8].

In this paper, the overall structure of SDN-oriented service function chain deployment is presented, and it is modeled as an integer linear programming mathematical model. Secondly, a heuristic search algorithm is designed to solve the deployment model in view of the difficulty that the current method fails to pay attention to both node and link resource requirements and underlying resource information. The heuristic search algorithm can be reduced to a two-level model, that is, SFC strategy—logical function chain and logical function chain–specific service path. For the SFC strategy, the logical function chain process is the dynamic orchestration combination of the application program to realize the VNF through the northbound interface. For the logical function chain, the specific service path process is to realize the reasonable allocation of underlying resources through the southbound interface.

**Definition 1. SFC strategy.**

The strategy includes a set of goals and a set of service functions, the target set represents the target of the processing action that needs to be performed; the service function set represents the service functions that the data message must traverse in sequence. The SFC strategy can be expressed as a set \( S = \{V_1, V_2, \ldots, V_m\} \), where \( V_i \) represents the service function sequence that the data message needs to pass through from the source node \( V_s \) to the destination node \( V_d \), where \( m \) represents the number of functions requested by the service [10].

**Definition 2. Logical function chain.**

The controller arranges the logical function chain formed by combining VNF modules according to the SFC strategy; the set \( F = \{f_1, f_2, \ldots, f_m\} \) can be used to represent the VNF logical function chain. The weighted directed graph \( G^v \) is used to represent all VNF deployable nodes and their contextual connections, marked as \( G^v = (N^v, L^v) \), where \( N^v \) represents the logical node collection of the VNF, namely, \( N^v = \{n^v_1, n^v_2, \ldots, n^v_i, n^v_{i+1}, n^v_{i+2}, \ldots, n^v_m\} \). \( L^v \) represents the set of virtual links between logical nodes, namely, \( L^v = \{n^v_i, n^v_j, \ldots \mid 1 \leq i, j \leq m\} \).

**Definition 3. Specific service path.**

According to the specified objective function as the VNF in the logical function chain and the virtual link to find the corresponding optimal placement position, form a specific service path from the source node to the destination node. The underlying network consists of all physical nodes and connection links; it can be represented by a weighted undirected graph \( G^p = (N^p, L^p) \), where \( N^p \) represents the set of underlying physical nodes, namely, \( N^p = \{n^p_1, n^p_2, \ldots, n^p_i, n^p_{i+1}, n^p_{i+2}, \ldots, n^p_k\} \); \( L^p \) represents the set of physical links between physical nodes, namely, \( L^p = \{n^p_i, n^p_j, \ldots \mid 1 \leq i, j \leq k\} \). SFC policy-logical function chain–specific service path process is used as an example to describe the instantiation process from initiating service requests to successfully
implementing service deployment and finally providing corresponding function services. First, the orchestration plane forms a logical function chain composed of four VNFS by invoking the northbound interface according to the tenant’s request. Second, the control plane, according to the underlying network resources status through south forwarding protocol control equipment and according to certain deployment strategy, maps the logical service chain to physical layer node, if the logic chain of service function mapping success assigned the corresponding instantiation resources, thus forming and meeting specific functionality, performance, and service path. In the specific service path, nodes with shadows represent physical nodes where VNF is deployed, while physical nodes without shadows only play the role of forwarding data [4].

2.3. Optimal Deployment Model Based on Integer Programming. The optimal deployment strategy is to comprehensively consider service resource requirements, network node resources, etc. and find the optimal position of the VNF node and virtual link deployment according to the specified objective function. This section is aimed at minimizing physical resources and establishing an integer programming model (ILP). For formal expression, the symbols used are shown in Table 1 [11].

### Table 1: Definition of main symbols.

| Symbol          | Meaning                                                                 |
|-----------------|------------------------------------------------------------------------|
| $c(n^i)$        | The computing resource requirements of VNF node $n^i$                  |
| $r(n^i)$        | The remaining computing resources of the physical node $n^i$           |
| $c(n^i_c, n^j_c)$ | Bandwidth resource requirements of the virtual link between VNF nodes $n^i_c$ and $n^j_c$ |
| $r(n^i_c, n^j_c)$ | The remaining bandwidth resources of the physical link $n^i_c$, $n^j_c$ |
| $D^r$           | Maximum transmission delay between two physical nodes                  |
| $D(n^i_c, n^j_c)$ | Delay of processing data packets at the node where the function is located |

Among them, $E(n^i)$ represents the set of all adjacent virtual links of VNF node $n^i_c$; $c(n^i_c)$ represents the amount of computing resources required for the instantiation of VNF node $n^i_c$; and $r(e^i_c)$ represents the bandwidth resource required for virtual link instantiation.

$$C(n^i_c) = c(n^i_c) \sum_{e^i_c \in E(n^i)} c(e^i_c).$$  \hspace{0.5cm} (1)

$$R(n^i_c) = r(n^i_c) \sum_{e^i_c \in E(n^i)} r(e^i_c).$$  \hspace{0.5cm} (2)

### 3. Algorithm Description

The two-step mapping algorithm in the traditional virtual network mapping process divides the mapping process into node mapping and link mapping; however, the logical function chain mapping in the service chain deployment process is different from the traditional virtual network mapping, needs to comprehensively consider the end system of the service chain, and instantiates features such as resource allocation and arrangement order. According to the characteristics of the service function chain deployment, design a heuristic search algorithm that sorts first and then is greedy, in order to quickly and efficiently solve the service function chain deployment model [12].

The current deployment of the service function chain is more of a single concern about node resource utilization or simply focuses on link resource utilization [13]. In order to determine the demand for VNF resources in the logical function chain and more accurately describe the remaining resources of the underlying physical node, the VNF comprehensive resource demand function $c(n^i_c)$ is given here, and the physical node integrates the concept of remaining resource function $r(n^i_c)$.

$$C(n^i_c) = c(n^i_c) \sum_{e^i_c \in E(n^i)} c(e^i_c).$$

Among them, $E(n^i)$ represents the set of all adjacent virtual links of VNF node $n^i_c$; $c(n^i_c)$ represents the current remaining computing resources of physical node $n^i_c$; and $r(e^i_c)$ represents the current remaining bandwidth resources of the physical link.

In order to simplify the search space of traditional heuristic algorithms and improve the efficiency of solving global resource allocation strategies, for the deployment model, the designed G-kSP algorithm is a sorted and then a greedy and efficient search method, the sorting method is used to simplify the search space of the algorithm, and the optimal service path can be obtained without performing a global search. In the greedy selection process, the physical node or link with the most remaining resources is considered as a greedy strategy; the greedy strategy has a direct impact on the operation of each subproblem, gets the optimal resource allocation strategy for each subproblem, and then quickly and efficiently approximates the model objective function [14].

### 4. Experimental Evaluation and Analysis

In order to verify the effectiveness of the proposed deployment algorithm (denoted as G-kSP), choose other two typical deployment algorithms for comparison. Select load, load balance, and three important deployment evaluation...
indicators and request acceptance rate and time complexity, in order to verify the effectiveness of the G-kSP algorithm; the load balance degree reflects the algorithm search and the degree of balance; the request acceptance rate reflects the search performance of the algorithm in the solution space; the request processing time reflects the computational performance of the algorithm [10].

4.1. Experimental Environment and Parameter Settings. This experiment is run on a Linux system PC configured with Intel Core i7-3770 3.60 GHz and 8 GB memory. The network topology is generated using GT-ITM tool, and the algorithm program is run through MATLAB software. Use a test example of a network topology with six identical physical nodes as the underlying infrastructure for experimentation, similar to a lightweight cloud data center network environment. The network topology consists of 6 nodes and 14 links (the number on the node represents the node label number); take node 1 as the data flow entrance and node 6 as the flow exit. Assuming that all nodes are deployed in a cloud data center and connect all nodes to be able to carry service functions, the physical node resources and the remaining resource capacity of the link bandwidth obey the random distribution of [1000, 1500]; the unit mapping cost of link and node is both 1. Each SFC request consists of different types of service functions, its quantity obeys the random distribution of [2, 5], the resource demand of each SFC node and link obeys the uniform distribution of [0.5, 1], the number of service types supported by the underlying network is set to 10, and each node randomly provides 1 to 5 of them [15].

4.2. Algorithm Performance Comparison

(a) Node load balance indicates the load accumulation of physical nodes and reflects the pros and cons of the algorithm in terms of node resource utilization; the smaller the value, the better; and the more balanced the load on each physical node, the better. Remember that the calculation formula of the load balance degree of the physical node is

$$\text{LB}_{n_i} = \sum_{n_j \in M(N)} \frac{c(n_j)}{r(n_j)}$$  

(3)

In the experiment, 10 to 100 SFC request strengths were generated, and the node load balance of the three algorithms was calculated, respectively, as shown in Figure 1.

As can be seen from Figure 1, the TS-based deployment method can obtain the maximum average load balance while at the same time, the maximum load balance of nodes is smaller, which shows that the algorithm has a better effect in balancing node load; on the contrary, the effect of the greedy algorithm is poor; the G-kSP algorithm is centered. The reason is that the TS algorithm uses the computing resource capacity of the underlying node as a selection strategy; in the iterative process, a better node selection plan can be searched, so that the resources of the node can be effectively used; the greedy algorithm gives priority to the nodes on the low-latency link, which is likely to cause the poor load balancing effect of some functional nodes [16, 17].

(1) The specific path load balance degree indicates the load accumulation of the entire service function chain and reflects the pros and cons of the algorithm in the utilization of resources of the entire network; the smaller the value, the better. Remember the calculation formula for the load balance degree of the specific execution path as

$$\text{LB}_{RSP} = \omega_n \sum_{n_j \in M(N)} \frac{c(n_j)}{r(n_j)} + \omega_l \sum_{(n_j, n_j) \in L(n_l, n_l)} \frac{c(n_j, n_j)}{r(n_j, n_j)}$$  

(4)

(2) The scaling factors $\omega_n$ and $\omega_l$ are used to adjust the emphasis of node load and link load. In the experiment, 10 to 100 SFC request strengths were generated; count the service path load balance of the three algorithms separately, as shown in Figure 2. It can be seen from Figure 2 that as the request arrival intensity increases, the amount of available resources decreases, and the curve gradually becomes flat. With the emergence of resource bottlenecks, the request acceptance rate gradually decreases, and the number of failures in service path construction increases. As the request arrival intensity increases, the deployment method based on the G-kSP algorithm can most effectively balance the load of the service path. Since neither the TS nor the greedy algorithm can allocate resources from the perspective of the global optimal path, as a result, the load of the network service path is relatively unbalanced; however, the greedy algorithm gives a higher deployment priority considering low-latency links; it easily causes frequent reuse of some links; as a result, it falls into a resource bottleneck prematurely, so the service path load balancing performance of the TS algorithm is better than that of the greedy algorithm.

In the experiment, 10 to 100 SFC request strengths were generated; count the request acceptance rate of the three deployment algorithms separately, as shown in Figure 3. As shown in Figure 3, under the same conditions, the average request acceptance rate of the G-kSP algorithm, TS deployment algorithm, and greedy deployment algorithm is about 95.4%, 92.3%, and 81.7%. In order to analyze the reasons, the G-kSP algorithm mainly considers the global optimal path, reduces the load balancing degree of the entire service function chain, improves the utilization of the underlying physical resources, and occupies less resource space, so as to leave the instantiation resources as much as possible for other requests in the queue to complete the deployment and
increase the request acceptance rate. The greedy algorithm mainly considers the utilization of link resources, increases the queue time and the underlying network load of node processing, and thus reduces the request acceptance rate; the TS algorithm mainly considers the node resources and can search the optimal deployment scheme through repeated iterative calculation, which improves the service request acceptance rate compared with the greedy algorithm.

5. Conclusion

The proposed service function chain deployment method can simultaneously pay attention to the resource utilization of nodes and links in the deployment process. First, the overall structure of SDN-oriented service function chain deployment is given for the problem of service function chain optimization deployment, reduces the overall
deployment structure to a two-level model of SFC strategy—logical function chain—specific service path, and is modeled as an integer linear programming mathematical model. The simulation results show that the SFC request intensity is generated for 10-100 times in the experiment, and the request acceptance rate of the three deployment algorithms is calculated, respectively, as shown in Figure 3. Under the same conditions, the average request acceptance rate of the G-KSP algorithm, TS deployment algorithm, and greedy deployment algorithm is about 95.4%, 92.3%, and 81.7%.

In this paper, feature selection is studied to a certain extent, but no attempt is made in classifier design. Therefore, to propose suitable classification methods and improve the determination of classification parameters will be the work of future research. In addition, the application of this method in the research field of intelligent product recommendation is the next key research direction.
Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was funded by the Hebei Province Key Research and Development Plan Self-Financing Project, application research of intelligent recognition in smart home communication protocol selection in artificial intelligence, Project No. 18210338, project leader: Li Xiaohui.

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