Seismic Data Query Algorithm

Subjects: Others

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Edge computing can reduce the transmission pressure of wireless networks in earthquakes by pushing computing functionalities to network edges and avoiding the data transmission to cloud servers. This also leads to the scattered storage of data content in each edge server, increasing the difficulty of content search.

edge computing seismic content lookup deep reinforcement learning

1. Introduction

Since the fifth generation of seismic devices, computer network technology has been introduced into seismic devices. A complete seismic telemetry acquisition system can be regarded as a relatively complex Local Area Network (LAN) system [1]. Seismic sensor network is essentially a special sensor distributed network, so it is necessary to use network research methods to study it, making the data transmission performance of the whole system optimal. In addition, current seismic devices have the characteristics of high density, large range and three-component acquisition. For wired seismic devices, simply increasing the number of instrument tracks will not only cause pressure on the bandwidth of the system, but also cause inconvenience to the construction. Wireless transmission has gradually become an important transmission method for seismic devices [2]. Due to the limited wireless bandwidth resources, if all the information generated by the seismic device is transmitted to the cloud server for unified management, it will waste a lot of communication resources.

In recent years, a new computing paradigm, mobile edge computing (MEC) [3] was proposed, which can move some of the computational functions to the network edge devices. In other words, researchers can perform distributed management of information on edge servers through MEC. In this way, the seismic device does not need to send all the information back to the cloud server for unified management, which can effectively reduce the transmission pressure [4]. However, this also introduces a new problem. Due to the lack of unified data management, it is difficult to quickly determine the location of data and content query also becomes a problem. So, fast data query in the wireless network of earthquakes supported by edge computing has become an important problem. But due to the complexity of the problem and the limited computing resources of edge servers, there are still many challenges to be solved.

Deep reinforcement learning (DRL) solutions [5] help take appropriate actions according to the state of environment and have achieved great success in various kinds of control tasks, which can provide a new idea to solve the task allocation problem in wireless networks of earthquakes. Reinforcement learning has many advantages, among which optimization of long-term average reward through training on historical data and adaptability to the environment. One of the most remarkable algorithms in DRL is deep Q-learning (DQN) [6], which can deal with models in continuous state spaces.

2. Edge Computing

As a new paradigm in computing and networking, edge computing is attracting extensive attention from academic and industry researchers. Some works have studied the computation offloading problem involving only a single edge node. For example, literature [7] focused on the energy consumption problem of computation offloading, and modeled it as a stochastic optimization problem with the goal of minimizing the energy consumption of task offloading while ensuring the average waiting queue length. The original problem was transformed by stochastic optimization method, and a dynamic energy-saving computation offloading method was proposed. Literature [8] formulated the task offloading problem, which joins uplink, downlink and computing resources allocation as a network of queues. The goal of optimization is to minimize the operational expenditure of computing resource providers. Then, authors transformed the problem into a Generalized Nash Equilibrium Problem and proposed two decentralized algorithms by introducing the penalty parameters to the coupling constraints. In [9], authors proposes an opportunistic access fog-cloud computing network to reduce latency and energy consumption of data transmission and computation. In this way, each mobile user can select the fog node through opportunistic access method. With the constraints of users' quality of service requirements, they jointly optimized both resource allocation and computation offloading, and designed an iterative algorithm to solve the problem. However, there are always multiple edge nodes in a system. Due to the different number of terminal devices and the different amount of computing tasks in the service range of each edge node, the single edge node offloading model is easy to lead to heavy computing pressure on some edge nodes, while some edge nodes are relatively idle. This results in the load imbalance between edge nodes, which affects the service experience [10].

Some of the latest research works consider the cooperation of multiple edge nodes to complete computing tasks. The authors of [11] proposed a computation offloading optimization mechanism for multi-edge device cooperation, modeled the optimization problem as a mixed-integer nonlinear programming problem, and designed a preference-based two-sided matching algorithm to reduce the overall task execution delay and achieve load balancing between edge devices. Literature [12] classifies application tasks in terms of computation amount and communication cost to help the computation offloading decision, and proposes an offloading algorithm based on greedy task graph partitioning, which uses greedy optimization method to minimize task communication cost. Reference [13] considers the trade-off between task delay during computation offloading and energy consumption during wireless transmission, and proposes an efficient and distributed predictive offloading and resource allocation scheme for multi-layer fog computing system by predicting system traffic, which can significantly reduce task delay with only a small amount of prediction information value. The authors of [14] designed a software-defined fine-grained multi-access edge computing architecture, which co-managed network and computing resources, and designed a two-level resource allocation strategy based on deep reinforcement learning to provide effective computing offloading services. Data privacy is also an important issue in computing offloading. Combined federated learning, authors [15] proposed a distributed learning framework for computation offloading with the goal of minimizing the task delay and energy consumption. As shown in **Table 1**, these computation offloading methods select the offloading location from all the edge nodes. But in seismic data query, information is stored separately and not all edge nodes store the required information, so the traditional computing offloading method is difficult to apply to this scenario.

Table 1. Comparison of existing works.

Literature	Cooperation of Nodes	Long-Term Average	Content Lookup
[7]	×	×	×
[8][9]	×	✓	×
[11][12]	✓	×	✓
[13][14][15]	✓	✓	×
our solution	✓	✓	✓

3. Wireless Network in Earthquakes

With the rapid development of Internet of Things devices, wireless networks are more and more widely used in earthquake and meteorological observation. Authors [16] showed how IoT devices based on wireless network can share the information (i.e., slightest vibration detected by earthquake warning devices, water level, soil moisture) globally, and carried out an in-depth analysis of it. The authors of [17] introduced the construction of Nankai Trough Seafloor Observation Network for Earthquakes and Tsunami (N-net). The system is a hybrid network of wired and wireless. Due to the low cost and rapid deployment, wireless sensor networks can provide remote monitoring and sensing for many critical scenarios, such as earthquakes and floods. The authors of [18] proposed an architecture based on wireless sensor networks in smart city applications and used unmanned aerial vehicles as offloading nodes. In [19], the authors introduced an open-source earthquake monitoring system, which was based on wireless network and energy-autonomous sensor nodes. Two emerging technologies in wireless network, LoRa and Message Queue Telemetry Transport (MQTT), was used in the system to reduce latency and packet delivery ratio. The authors of [20] designed an energy consumption scheduling scheme based on longitude and latitude coding algorithm and differential evolution algorithm to reduce overall energy consumption of wireless sensor network in the process of earthquake monitoring. In order to improve the utilization rate of network resources, they formed three-layer network architecture by building intermediate service layer to connect sensor nodes and sink nodes. Authors [21] proposed a low-cost, low-power and cloud-base seismic alert system. In order to process tasks based on computation and communication resources in the cloud, the system leveraged existing wireless networks to minimize costs and maximize communication speed. Although wireless networks have gradually become an important transmission method for seismic devices, there are few studies on seismic data query in wireless network.

4. Quick Lookup Mechanism

Focusing on lookup speed, memory consumption and false positive probability, the paper [22] proposed a smart mapping model named Pyramid-NN via neural networks to build an index algorithm, which was trained by real NDN names offline and preset in content routers in the future, that can not only reduce the memory consumption and the probability of false positive, but also ensure the performance of real NDN name lookup. To improve the performance of content lookup, the authors of [23] extended the cuckoo filter to integrate a Bloom filter, which is used to improve the performance of insertions. The algorithm, which was adjusted to the bucket size, can preserve the support for deletion of the original cuckoo filter without the additional memory accesses for lookup operations. To effectively remove false positives while completing all queries in a single memory access, the authors of [24] proposed an adaptation scheme based on one memory access bloom filter. The proposed algorithm is very suitable for the case of low memory bits per element. In [25], the authors observed that many exact-pattern-matching-intensive workloads can benefit from a DRAM-based processing-in-memory (PIM) architecture, and extended the model with several cost-effective modifications to improve the efficiency of content lookup. For the flow table lookup problem, the authors of [26] proposed a new flow table lookup scheme based on bloom filters and RAM, which offers a good compromise between cost and performance. The authors also verified the results by linearly searching the contents of secondary RAM to solve the problem of false positives of primary bloom filter.

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