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Distribution of teaching surveillance video via edge computing

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The generation, processing and distribution of multimedia data from video are increasingly toward the edge of the network with the development of mobile and industrial network. The uncertainty of user behavior and limited system resources have become a major challenge for network video services, for example, the distribution of teaching surveillance video. It is a hot spot to support network video services and content distribution with lower latency and higher bandwidth requirements by using the computing, storage, and network resources at the edge of network. In this paper, we first analyze the challenges which are faced in video distribution based on edge computing; then propose a framework for teaching surveillance video content distribution through the network, storage, and computing capabilities of edge computing; lastly provide an edge caching architecture and a cache update strategy by using a LSTM network. The experimental results demonstrate the proposed framework is more efficient than previous ones.

KEYWORDS

edge computing, LSTM, teaching surveillance video, video distribution

1 | INTRODUCTION

With the explosion of global network data, the video has become the main carrier of network traffic. The multimedia is becoming a "killer" application in the Internet. The Cisco Network Forecast Index shows that 75% of global data traffic in 2017 is video content, and this number is predicted to reach 82% in 2022. Additionally, with the explosion of the amount of video data, multimedia video content is showing the following three trends: high quality, real-time interactive, and video service mobility. Network multimedia, especially network video, not only experiences explosive growth in data traffic, but also brings new challenges of content distribution.

Because of the explosive growth in demand for video distribution, it is difficult to support a large demand growth for current speed of core network and distribution network upgrading. Meanwhile, users' expectation for the quality of multimedia video services continues to increase, that is, high bit rate and low latency network content distribution. The current backbone network overload and network congestion often happen. A potential solution for content distribution is to utilize the network, computing, and storage capabilities of edge-side devices.

Edge computing refers to the use of network, computing, and storage capabilities on the side close to the source of the request to provide the nearest end service.[1] In edge computing, the user request is initiated on the edge side, and the service is executed. Therefore, edge computing brings a faster network service response and saves bandwidth. The edge computing reduces the bandwidth pressure of video content on the

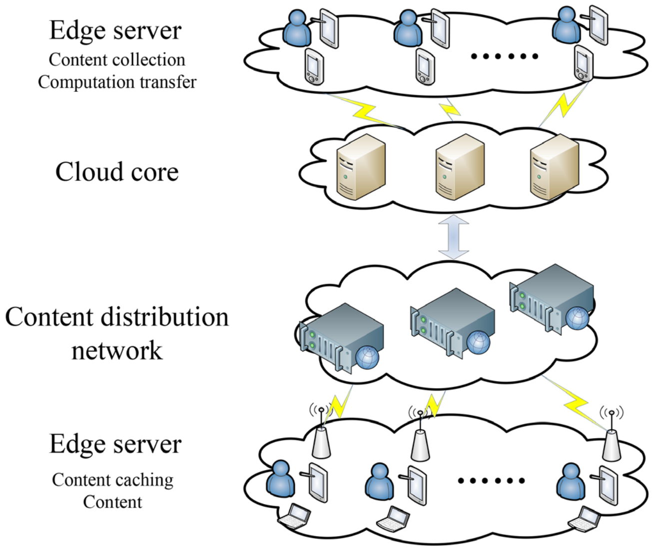

FIGURE 1 The architecture of edge computing for video distribution

backbone network and provides users with a better interactive experience. Edge computing becomes a new content distribution scheme.

In 5G, mobile edge computing (MEC) has become an important enabling technology and the edge devices with computing and storage capabilities in the communication provides ultra-low latency and reliable services for the applications, such as Internet of Vehicles, Industrial Internet, and VR/AR. On the other hand, WiFi hotspots and dedicated edge storage devices with computing storage capabilities provide the infrastructure of edge computing to make content distribution become possible. Compared with previous content distribution methods, the content distribution on edge side can be close to user, which can greatly reduce the transmission overhead of the core network and user delay. By using the storage space of the edge node,[2] the content can be cached in the local edge node and distributed on the edge node. Additionally, the time-consumed services, such as video transcoding and distributed intelligent decision-making, can be computed on edge node as well. In this paper, we use edge computing to solve the content distribution for teaching surveillance video.

2 | TEACHING SURVEILLANCE VIDEO DISTRIBUTION VIA EDGE COMPUTING

In this section, we use edge computing to distribute content for teaching surveillance video. First, we will briefly introduce the framework of buffer edge node for teaching surveillance video distribution. Then, we use a long-short term memory (LSTM) network as updating cache strategy.

2.1 | Architecture of teaching surveillance video distribution via buffer edge node

Edge computing devices can be used to cache video content with the help of their storage capabilities. Video distribution through edge computing has the following merits: first, it saves the core network bandwidth; second, it reduces the delay for users to access video content. The multimedia video content requires high bandwidth, such as real-time interactive live broadcast and ultra-definition video. The buffer edge node can satisfy the bandwidth requirement.

The edge computing architecture[3] emphasizes that the edge service nodes with storage, computing and network resources are densely and widely distributed in the places which are close to the end users. The edge service nodes serve the close users to save backbone network bandwidth, reduce service delay, and provide better quality of service. The video distribution architecture based on edge computing mainly includes an edge distribution network for the "last mile", and a content collection network for the "first mile". The architecture is illustrated in Figure 1.

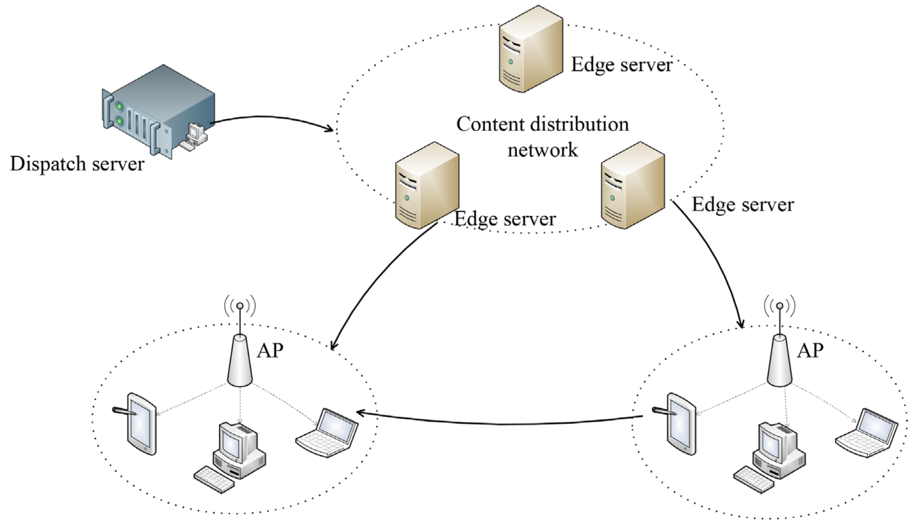

FIGURE 2 The architecture of content distribution on the edge node

In the content collection network for the "first mile", the video transmission includes two steps: video upload and video distribution. In video upload, the video stream generated from the video anchor is uploaded to the server, which is called the "first mile" of network transmission. In video distribution, the video stream is transmitted from the server to the audience in the live broadcast room. Today's mobile live broadcast services usually use traditional CDN solutions to solve the video distribution problem, but these solutions rarely pay attention to the issues of improving the video upload quality.

In the edge content distribution network for the "last mile", the quality of the last hop usually determines user experience. The "last mile" of edge distribution network uses the caching capabilities of edge nodes to deploy content to the nodes near users for caching and distributing. Therefore, the users can get better experience via getting content from near nodes. Edge content distribution needs to study content replication and cache replacement strategies for edge nodes. The content replication strategy mainly solves the problems of what content is cached in the edge node and how to deploy the cached content in the edge node when the content is cached.

For a large number of scattered edge nodes, the content cache replication strategy needs to balance user experience and system overhead. To achieve a low latency and high bandwidth overall user experience, it is necessary to copy as much content from the server to the edge node as possible to ensure that most user requests can be served by the edge node. However, copying content from the server to the edge node will result in traffic overhead and excessively fine-grained scheduling.

This paper proposes an edge node cache strategy based on region division. Our strategy includes three main modules: edge resource on-demand deployment, global resource scheduling and content collaborative replication.

In edge resource on-demand deployment, the edge node deployment is formalized as a facility location problem (FLP) by considering both deployment cost and user experience. Therefore, we need to minimize the total node deployments and user request allocations. The content distribution architecture based on the edge node cache is shown in Figure 2.

In the regional division scheduling algorithm, the edge nodes in the same region are regarded as a whole to perform a content copy to eliminate redundant transmission for organizing and managing the deployed edge nodes. The Voronoi-like region segmentation algorithm is used to solve the joint optimization problem of user experience and replication cost. The inter-content reduces the core network peak overhead by 38% and improves the user experience by 40% by using active content replication strategy based on regional user request prediction and considering server bandwidth status and content popularity similarity in the adjacent regions.

2.2 | Cache update strategy based on LSTM

For edge cache replication, many methods have been proposed. For instance, Ma et al[4] carried out data measurement on real data sets to prove the effectiveness of edge cache, and designed a cache strategy based on the measurement results.

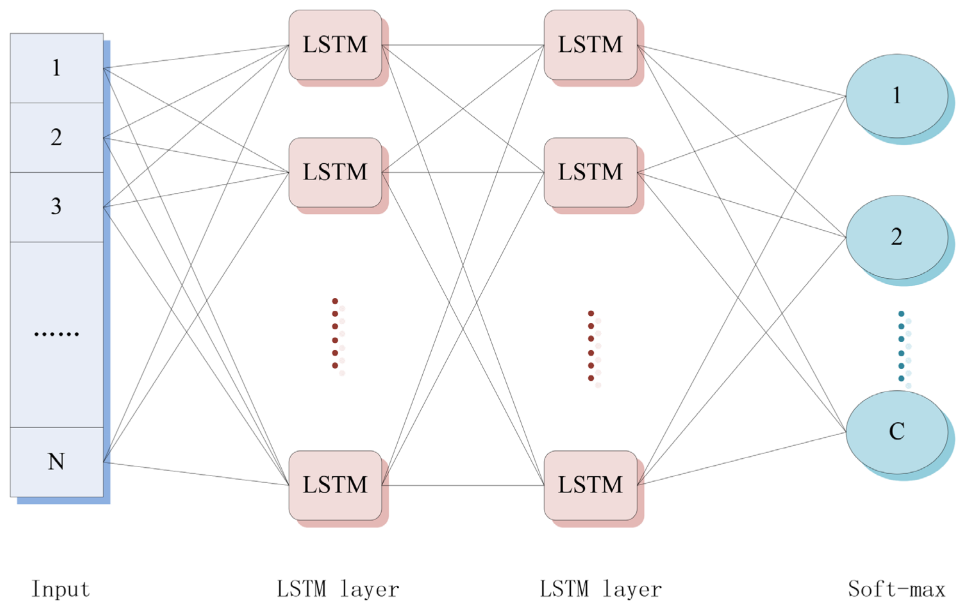

FIGURE 3 The architecture of cache update strategy based on LSTM

Leconte et al[5] investigated the challenges of caching in small areas, estimated content popularity and inferred popular content from small size samples in real time, and designed a threshold strategy based on lifetime to estimate the popularity of dynamic content. Liu et al[6] used contract theory to optimize the revenue of service providers, content providers and users in cache services. Li et al[7] introduced an effective cooperative caching mechanism between small base stations. For edge cache replacement, the currently deployed cache algorithms in actual systems include FIFO, LFU, LRU, and their variants. In order to overcome the shortcomings of these algorithms, Einziger et al[2] proposed a strategy to determine the content which was updated according to the real-time popularity of the content in the cache. However, they did not consider the changing trend of content popularity. Li et al[8] proposed a dynamic popularity-driven cache replacement strategy with the help of online learning, the popularity of each requested content was predicted, and the least popular content in the local cache was replaced according to the prediction result.

The cache update strategy and cache-based replacement strategy based on manual feature extraction both rely on manual intervention or are difficult to cope with changing content access patterns. In order to address the weakness of manual methods, this paper proposes a cache update strategy based on the deep long-term and short-term memory (LSTM) network model. The LSTM model can automatically learn the cache update strategy from the content request sequence without human intervention and data preprocessing. The cache update architecture based on LSTM network is illustrated in Figure 3.

The cache update system is shown in Figure 4. Deep-cache is a cache replacement strategy based on deep neural networks. It can automatically learn the cache strategy from the request sequence in real time without using any data preprocessing or feature engineering. Experiments show that Deep-cache can increase the cache hit rate by 20% to 30%.

3 | EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we will try to solve the teaching surveillance video distribution by our framework. First, we construct a simulation system to compare visiting teaching surveillance video from cloud center directly. Then, we compare the performance by using edge computing with caching when different cache update strategies are adopted.

We collect 8000 teaching surveillance videos from closed-circuit television (CCTV) center. Each video lasts 15 minutes. The visiting times during past 25 hours are used as the video's popularity. The future popularity is predicted by a LSTM model which is learnt by historical records. The experimental results are reported in terms of the bandwidth consumption and the statistics of user experience in Table 1.

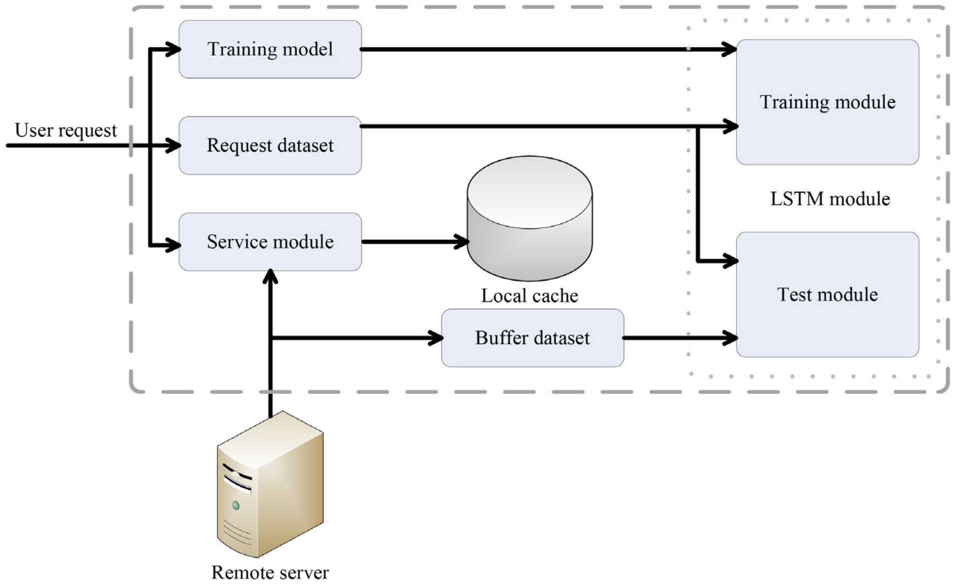

FIGURE 4 The architecture of cache update strategy based on LSTM

TABLE 1 Experimental results comparison of teaching surveillance video watching

		Bandwidth consumption (%)	CDF
Cloud center		37.43	0.63
Edge computing	FIFO	21.64	0.41
	LFU	21.37	0.39
	LRU	21.51	0.38
	LSTM	19.28	0.31

From Table 1, it can be found that LSTM only consumes 19.28% bandwidth and the associated CDF caused by network failure is 0.31, both of which are lower than the relevant indicaters of cloud center, FIFO, LFU, and LRU. By adopting edge computing technique and using LSTM as cache update strategy, both bandwidth and user experience are improved.

4 | CONCLUSIONS

The bandwidth and user experience impacted by network failure are two key issues in teaching surveillance video distribution. In a complex application environment, the uncertainty of user behavior and system resources has become a major challenge for network video services. One way to solve this issue is to put the computing, storage, and network resources at the edge of the network to ensure the distribution of video content and support network video services with lower latency and lower bandwidth requirements. In this paper, we propose a framework based on edge computing and use a LSTM network as cache update strategy to the teaching surveillance video content distribution. The LSTM network is a offline model which can not be updated according to the videos request. In the future work, we plan to use an online model as cache updating algorithm instead of LSTM network.

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