SIMULATION OF VIDEO ANALYTIC APPLICATIONS USING DEEP LEARNING

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ABSTRACT

The traditional approaches for video analytics are only in the cloud that requires high latency and more network bandwidth to transform data. To minimize these problems, Video Analytic Data Reduction Model (VADRM) using deep learning by implementing CNN-based edge computing modules is proposed. By implementing on CNN-based video processing, VADRM divides the video analytic jobs into smaller tasks for small processing edge nodes. Examining this technique and finding a solution in a real system is very expensive. Therefore, the results of the prototype model is used for the simulation to test the problem and alleviate the bottlenecks. The proposed solution is to develop an architecture that integrates IoT with edge and cloud to minimize network bandwidth and latency. In this work, simulation is performed in iFogSim and simulated results show that the integration of the edge and cloud based model using VADRM produces 85% more performance than only cloud-based approach.

1 INTRODUCTION

In a common video analytic system, video data is directly transferred to the cloud in which video frames are extracted and objects are detected and recognized. The problem of the centralized approach is high latency and more network bandwidth to transfer data into the cloud. The video analytics jobs are large applications that is why they are called edge computing killers (Ananthanarayanan et al. 2017). The concept of division of the video analytic application into subtasks has been presented in (Pudasaini and Abhari 2020), but we did not use simulation for the performance test. In this work, the performance using VADRM is measured using iFogSim simulator.



Figure 1: Video analytic Data Reduction Model (VADRM).

2 SIMULATION AND RESULTS

The VADRM is explained in figure 1. In this model, video analytic is divided into four modules: motion detection (s1), object detection (s2), object tracking (s3), and pattern recognition (s4). The motion detector

Pudasaini

receives the raw video stream and detects the motion of the moving objects, then passed to the object detector to detect the objects. The detected objects are passed to the object tracker to track the path of the moving objects. Finally, the object tracker sends the tracking points for pattern recognition.

The simulation is performed in iFogSim simulator. The real video data are processed by implemented VADRAM prototype and the resulted data are passed into a simulator. The average data size deduction by using VADRM with real videos is 97%. The workload based on MIPS are passed as the input for each module s1 to s4. Case 1(Edge and Cloud): The modules s1, s2 and s3 are performed in edge and s4 is performed in the cloud. Case 2 (Edge only): All the modules of video analytic application are performed on edge devices. Case 3 (Cloud only): All the module are processed in the cloud. The resource utilization, latency, bandwidth and energy consumption are measured that are shown in figure 2. The network bandwidth, resource utilization and latency of proposed approach (edge and cloud) is more than 85% better than only cloud-based approach. The energy consumption is slightly improved in our proposed approach.



Figure 2: Comparison results.

3 CONCLUSION

The integration of the edge computing and the cloud computing is the main paradigm for video analytics applications. In this work, the new approach for simulation of video analytics is proposed for edge devices and the cloud. A prototype for division of video analytic application into number of phases called VADRM is developed to reduce the size of video data into consecutive phases. VADRM is implemented by CNN architectures and the large numbers of moving vehicles were processed by it. Finally the data based on VADRAM modules are used in iFogSim simulator. By the simulation, the VADRM model shows more than 85% efficient when using edge computing and cloud approach in comparison to only cloud approach.

REFERENCES

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