Adaptive Resource Management for Analyzing Video Stream from Globally Distributed Network Cameras

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Abstract

There has been tremendous growth in the amount of visual data available on the Internet in recent years. One type of visual data of particular interest is produced by network cameras providing real-time views. Millions of network cameras around the world continuously stream data to viewers connected to the Internet. This data may be used by a wide variety of applications such as enhancing public safety, urban planning, emergency response, and traffic management which are computationally intensive. Analyzing this data requires significant amounts of computational resources. Cloud computing can be a preferred solution for meeting the resource requirements for analyzing these data. There are many options when selecting cloud instances (amounts of memory, number of cores, locations, etc.). Inefficient provisioning of cloud resources may become costly in pay-per-use cloud computing. This paper presents a method to select cloud instances in order to meet the performance requirements for visual data analysis at a lower cost. We measure the frame rates when analyzing the data using different computer vision methods and model the relationships between frame rates and resource utilizations. We formulate the problem of managing cloud resources as a Variable Size Bin Packing Problem and use a heuristic solution. Experiments using Amazon EC2 validate the model and demonstrate that the proposed solution can reduce the cost up to 32% while meeting the performance requirements.

KEYWORDS: Visual data analysis, network cameras, cloud computing .EC2,opencv

I INTRODUCTION

Over the past decade, the utilization of visual data, such as images and videos, for scientific analysis to address real-world challenges has seen a significant surge. Network cameras, in particular, have garnered attention for their ability to generate continuous real-time video data with diverse content.With millions of network cameras deployed annually, the video analysis market has experienced rapid growth, estimated to surpass $1.2 billion by 2017.Various applications, including enhancing public safety, aiding emergency responses, and facilitating surveillance, rely on the extensive visual data provided by network cameras. These cameras, encompassing both indoor and outdoor environments such as traffic cameras and those in shopping malls, are publicly accessible and owned by different organizations. Notably, the

configurations of these network cameras are fixed and cannot be modified. The demands of such applications often entail high-resolution video data, long-duration analysis, data aggregation from multiple cameras, and high frame rates, presenting significant "big data "challenges requiring substantial computational resources. Cloud computing emerges as a promising solution to meet these resource needs by leveraging multiple cloud instances equipped with ample cores and memory. Applications often require streaming data from network cameras worldwide, necessitating efficient data streaming mechanisms considering geographical distances. Cloud service providers offer diverse VM instances with varying specifications and geographical locations, typically following a "pay-per-use" pricing model. However, effectively managing resources poses challenges, as computational requirements fluctuate based on factors like time of day and scene content. Addressing this challenge, Adaptive Resource Management for Video Analysis in Cloud (ARMVAC) method is proposed. ARMVAC determines optimal cloud instance configurations (type, location, quantity) to fulfill performance requirements while minimizing costs. It considers Motion JPEG (MJPEG) as the video data format and incorporates network distances between cameras and cloud instances, as well as the relationships between frame rates and CPU utilization on different VM types. The approach involves modeling the resource selection problem as a Variable Size Bin Packing Problem (VSBPP) and employs a heuristic algorithm to find solutions. ARMVAC predicts the maximum number of streams analyzable on various cloud instances for specific analysis programs. It dynamically adjusts resource allocation based on performance requirements and resource utilization, resulting in potential cost savings of up to 62% compared to alternative cloud resource selection strategies.

II LITERATURE SURVEY

Cloud computing has revolutionized the way organizations deploy, manage, and scale their IT infrastructure, offering unprecedented flexibility, scalability, and cost-effectiveness. This literature survey explores various aspects of cloud computing, particularly in the context of video analysis and surveillance systems.

1. **Amazon Auto Scaling** [1]: Amazon Web Services (AWS) Auto Scaling allows users to automatically adjust the capacity of their

Amazon EC2 instances based on demand, ensuring optimal performance and cost efficiency.

2. **Amazon EC2** [2]: Amazon Elastic Compute Cloud (EC2) is a web service that provides resizable compute capacity in the cloud. It enables users to quickly scale up or down their compute resources as needed.

3. **Amazon EC2 Pricing** [3]: This resource provides information on the pricing model for Amazon EC2 instances, including on-demand, reserved, and spot instances, as well as pricing for additional services and features.

4. **Motion JPEG Video Codec** [4]: This resource discusses the Motion JPEG (MJPEG) video codec, which is commonly used in video surveillance systems for its simplicity and efficiency in encoding and decoding video streams.

5. **netem, Network Emulation Utility** [5]: netem is a network emulation utility that allows users to simulate various network conditions, such as latency, packet loss, and bandwidth restrictions, to test the performance of distributed systems like cloud-based video surveillance platforms. 6. **Network camera and video analytics market
** [6]: This market report provides insights into the growth and trends in the network camera and video analytics market, highlighting the increasing adoption of visual communication technologies.

7. **The OpenCV library** [7]: OpenCV is a popular open-source computer vision library used for image and video analysis. It provides a wide range of algorithms and tools for tasks such as object detection, recognition, and tracking.

8. **A computational approach to edge detection** [8]: This seminal paper by John Canny presentsa computational method for detecting edges in images, which is a fundamental step in many computer vision applications, including video analysis.

9. **Adaptive cloud resource allocation for analyzing many video streams** [9]: This research paper proposes an adaptive resource allocation algorithm for efficiently analyzing multiple video streams in the cloud, optimizing resource utilization and cost.

10. **Analysis of large-scale distributed cameras using the cloud** [10]: This paper explores the use of cloud computing for analyzing large-scale distributed camera networks, highlighting the benefits and challenges of leveraging cloud resources for video surveillance.

11. **CPLEX: Users manual for CPLEX** [11]: This manual provides detailed documentation for IBM's CPLEX optimization software, which is widely used for solving complex optimization problems, including resource allocation and scheduling in cloud computing environments.

12. **Efficient lower bounds and heuristics for the variable cost and size bin packing problem
** [12]: This research paper presents efficient algorithms for solving the variable cost and size

bin packing problem, which has applications in resource allocation and scheduling in cloud computing.

13. **Variable sized bin packing** [13]: This paper discusses algorithms for efficiently packing variable-sized items into bins, a problem commonly encountered in resource allocation and provisioning in cloud environments. 14. **Incident-supporting visual cloud computing utilizing software-defined networking** [14]:

This study explores the use of software-defined networking (SDN) for incident-supporting visual cloud computing, enhancing the scalability and flexibility of cloud-based video surveillance systems. 15. **Resource allocation for service composition in cloud-based video surveillance platform** [15]: This paper proposes a resource allocation framework for optimizing the performance of cloud8 based video surveillance platforms, considering factors such as service composition and quality of service requirements.

16. **Efficient resource management for cloud-enabled video surveillance over next-generation network** [16]: This research focuses on efficient resource management techniques for cloud enabled

video surveillance systems deployed over next-generation networks, addressing challenges such as bandwidth constraints and latency.

17. **Empirical prediction models for adaptive resource provisioning in the cloud** [17]: This study develops empirical prediction models for adaptive resource provisioning in cloud environments, enabling proactive scaling based on workload predictions and performance metrics.

18. **A system for large-scale analysis of distributed cameras** [18]: This paper presents a system architecture for large-scale analysis of distributed cameras, leveraging cloud computing and distributed processing techniques to analyze video streams efficiently. This literature survey highlights the diverse range of research and technologies in cloud computing and video analysis, underscoring the importance of efficient resource management, optimization algorithms, and scalable architectures in building robust and scalable video surveillance systems in the cloud.

III EXISTING SYSTEM

There has been tremendous growth in the amount of visual data available on the Internet in recent years. One type of visual data of particular interest is produced by network cameras providing real-time views. Millions of network cameras around the world continuously stream data to viewers connected to the Internet. This data may be used by a wide variety of applications such as enhancing public safety, urban planning, emergency response, and traffic management which are computationally intensive. Analyzing this data requires significant amounts of computational resources. Cloud computing can be a preferred solution for meeting the resource requirements for analyzing these data. There are many options when selecting cloud instances (amounts of memory, number of cores, locations, etc.). Inefficient provisioning of cloud resources may become costly in pay-per-use cloud computing.

Disadvantages

Inefficient Cloud Resource Provisioning for Video Stream Analysis: The current landscape faces challenges in efficiently provisioning cloud resources for the analysis of video streams obtained from globally distributed network cameras. As the demand for real-time insights from these camera feeds grows, there's a lack of optimized strategies to select and allocate cloud instances effectively.

This inefficiency arises due to several factors:

1. Lack of Granular Resource Allocation Models
2. Complexity in Resource-Performance Relationships
3. Dynamic Nature of Video Content
4. Cost-Efficiency vs. Performance Trade-offs

IV PROBLEM STATEMENT

The surge in real-time visual data generated by network cameras presents a pressing computational obstacle. This study focuses on strategically selecting cloud instances to address this challenge by optimizing resource allocation. The primary goal is to achieve cost efficiency without sacrificing performance in data analysis applications. To do so, the study aims to understand the intricate workload characteristics and computational requirements of different tasks. By analyzing usage patterns and demands, researchers can identify cloud instances best suited for real-time visual data processing.

A key aspect of this study involves cost-performance modeling. Through this modeling, researchers can evaluate various cloud configurations to pinpoint the most effective solutions. Factors like processing speed, memory capacity, and pricing structures are carefully considered to enable organizations to make informed decisions aligned with budget constraints and performance needs.

V PROPOSED SYSTEM

This paper presents a method to select cloud instances in order to meet the performance requirements for visual data analysis at a lower cost. We measure the frame rates when analyzing the data using different computer vision methods and model the relationships between frame rates and resource utilizations. We formulate the problem of managing cloud resources as a Variable Size Bin Packing Problem and use a heuristic solution. Experiments using Amazon EC2 validate the model and demonstrate that the proposed solution can reduce the cost up to 62% while meeting the performance requirements.

Advantages.

Adaptive Resource Allocation Framework

The project aims to develop an adaptive resource allocation framework specifically tailored for the efficient analysis of video streams sourced from globally distributed network cameras. The key components of this proposed solution include:

1***.Dynamic Resource Allocation Algorithm:*** This algorithm dynamically distributes computing resources such as CPU, memory, and bandwidth based on the current workload and resource availability. It aims to optimize resource utilization while ensuring timely processing of video streams.

2.***Performance-Resource Modeling***: This involves creating mathematical models that correlate the performance of the system (e.g., processing speed, latency) with the allocation of resources. These models help in predicting system behavior under different conditions and guide resource allocation decisions.

3.***Variable Size Bin Packing Problem Formulation***: Video streams often vary in size and complexity, presenting a challenge in efficiently packing them into processing units. This component focuses on formulating algorithms to optimally allocate resources by efficiently packing variable-sized video streams into processing units or containers.

4. ***Cloud Computing Infrastructure Integration***: Leveraging cloud computing infrastructure enables scalable and flexible resource allocation. This component involves integrating the framework with cloud platforms such as AWS, Azure, or Google Cloud to dynamically provision resources as needed.

5. ***Real-time Adaptation and Optimization***: The framework continuously monitors system performance and workload characteristics to adapt resource allocation in real-time. It employs feedback loops and adaptive algorithms to optimize resource allocation dynamically as conditions change.

6. Validation and Experimentation: This component involves designing experiments and validation procedures to assess the effectiveness and efficiency of the resource allocation framework. It includes testing the framework under various scenarios and workload conditions to validate its performance.

7***. User Interface and Monitoring***: Providing a user-friendly interface enables administrators to monitor system status, resource utilization, and performance metrics in real-time. It includes features for configuring resource allocation policies, setting thresholds, and receiving alerts.

8. ***Privacy and Security Measures***: Given the sensitive nature of video data, this component focuses on implementing measures to ensure privacy and security. It includes encryption mechanisms, access controls, and data anonymization techniques to protect the integrity and confidentiality of video streams and processing results.

VI IMPLEMENTATION

Camera Management Module:

This module handles the management of network cameras deployed globally. It allows users/administrators to define the total number of network cameras participating in the system Simulation.

Cloud Instance Management Module:

Manages the cloud instances available for processing the video streams from the network cameras. Users/administrators can assign cloud instances to individual cameras based on factors such as frame rate requirements and cost.

Cost Calculation Module:

Calculates the cost associated with each cloud instance based on its proximity to the camera and the frame rate requirements. This module utilizes the 'Best First Decreasing Sort' algorithm to sort the cloud instances based on location, instance type, and cost to choose the instance with the minimum cost without compromising quality.

Video Processing Module:

Handles the processing of uploaded videos by converting them into frames and sending them to the selected cloud instances for analysis. This module utilizes the OpenCV library to detect whether each frame contains a person or not.

Simulation Control Module:

Manages the simulation of the system by initiating the uploading of videos, playing the video streams, and sending frames to cloud instances for processing. It provides controls to start and stop the simulation process.

Visualization Module:

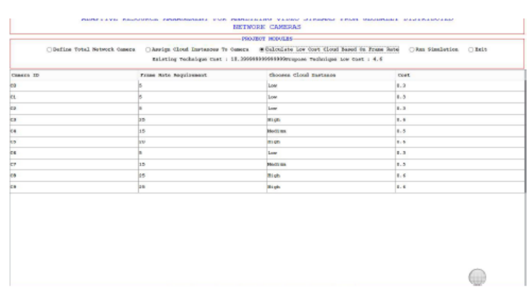
Provides graphical user interface elements for visualizing the simulation process, including the Representation of network cameras, cloud instances, and the detection of persons in video frames. It also generates graphs to display the cost details of different techniques used for instance selection.

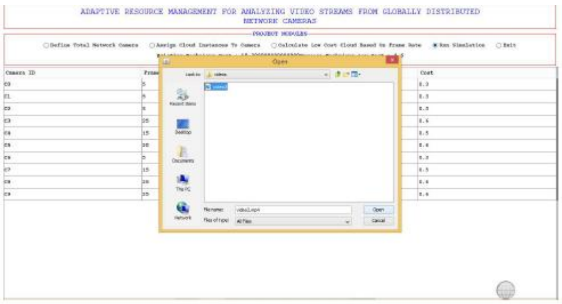
Reporting Module:

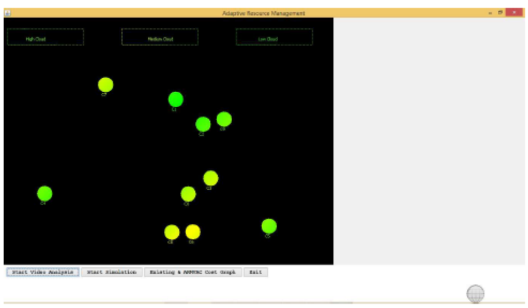
Generates reports on the performance of the Adaptive Resource Management system, including cost savings achieved by using the ARMVAC technique compared to existing techniques. It may also provide insights into the efficiency of resource utilization and the quality of video processing.

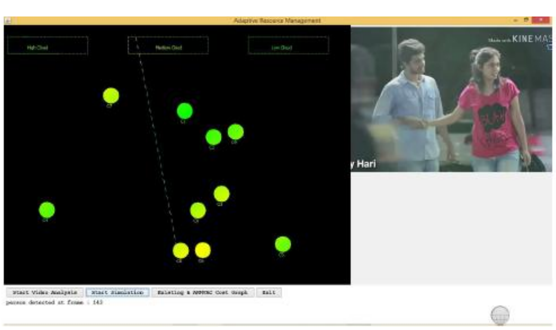
VII RESULTS

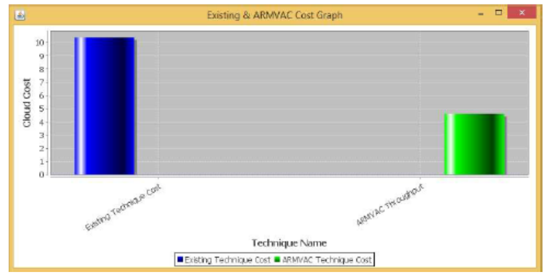
Screenshort-8.1.2

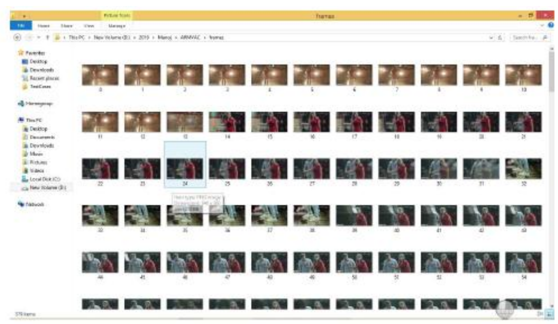












VIII CONCLUSION

This paper introduces ARMVAC, an innovative adaptive resource manager designed to select cost-effective cloud instances for analyzing MJPEG data from a globally distributed network of cameras. The system is engineered to handle inputs such as analysis programs, the required number of cameras, their geographical locations, the target frame rates, and the durations of the analyses. Based on these inputs, ARMVAC determines the optimal types, locations, and number of cloud instances needed to achieve the desired frame rate for all cameras. The core functionality of ARMVAC relies on a predictive model that estimates the maximum number of streams that different types of instances can analyze. This model is crucial for ensuring that the selected cloud instances can handle the data processing demands without compromising performance. To validate the effectiveness of ARMVAC, we conducted evaluations using Amazon EC2 cloud instances. Our findings revealed that ARMVAC consistently achieved the target frame rate on all cameras across various input scenarios. This consistency highlights the robustness of ARMVAC in meeting performance requirements. Moreover, ARMVAC demonstrated significant cost savings, reducing overall expenses by up to 62% compared to four other reasonable strategies (ST1 - ST4) for cloud configuration selection.

This cost efficiency is a major advantage, making ARMVAC a valuable tool for managing cloud resources in a financially sustainable manner. The evaluation also confirmed that our method is systematic and not ad-hoc, which means it can be applied to a variety of analysis programs beyond those initially tested.

In the context of future developments, we aim to extend ARMVAC's capabilities to handle more Complex and resource-intensive analysis programs. Specifically, we plan to optimize ARMVAC for memory-intensive, bandwidth-intensive, and I/O-intensive tasks. This enhancement will broaden the applicability of ARMVAC, allowing it to manage a wider range of data processing requirements.

Another important area of future work involves improving the adaptive launching of instances. Currently, ARMVAC adjusts cloud resources based on initial conditions, but we aim to make it more responsive to real-time changes in workload and system performance. This dynamic adjustment will ensure that ARMVAC can maintain optimal performance even as conditions fluctuate during the analysis process.

Additionally, we plan to investigate the impact of adaptive streaming technologies, such as H.264, on resource selection and management. H.264 streams are known for their varying bit rates and compression efficiency, which can influence the computational load on cloud instances. Understanding these effects will allow us to refine ARMVAC further, making it more adept at handling diverse streaming scenarios and improving its overall efficiency.

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