Quality of Experience Aware Collaborative Augment Reality System (Q-CARS)

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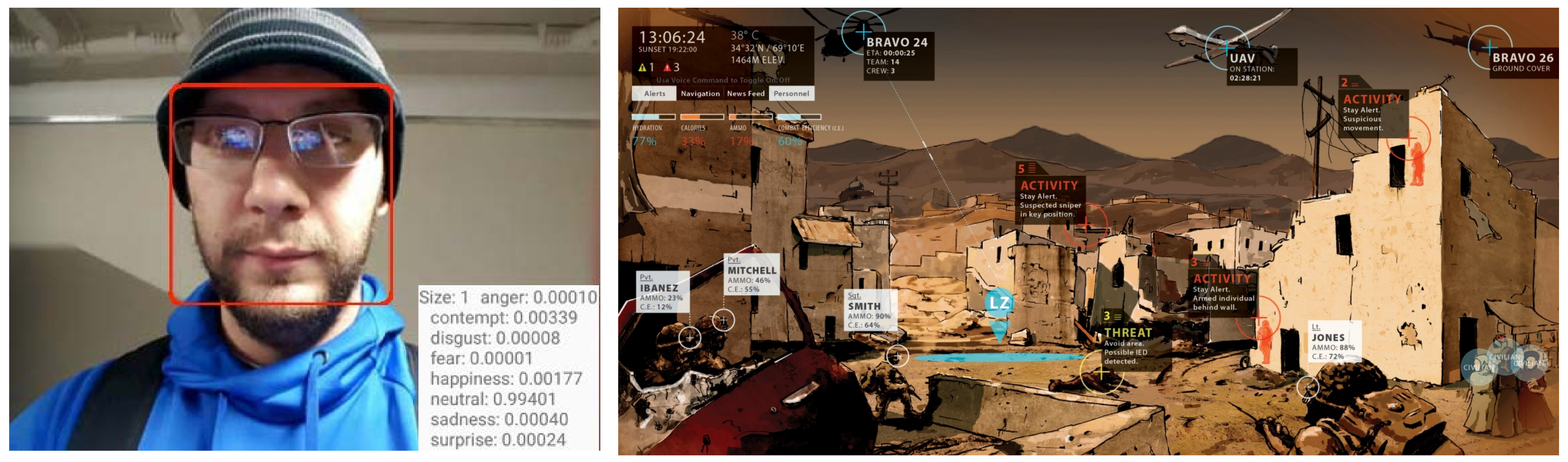
Abstract

Achieving high QoE (Quality of Experience) for AR applications on a mobile device is challenging because the required advanced computer vision and machine learning algorithms are computationally intensive by nature. Hence, some task for AR applications must be offloaded to more powerful remote servers. Offloading for mobile applications remains an active area of research. In the context of mobile AR applications which requires continuous processing, offloading algorithms must be applied with care due to the high wireless network latencies. In fact, there are only a few mobile AR QoE frameworks to take wireless network conditions into consideration, and none of them studied the relationship between mobile AR QoE and wireless channel status that impacts each other along the time scale. In this project, we propose **Q-CARS** system, which will provide real test results that facilitate the design of the wireless network that enhances the support of QoE in AR systems.

Motivation



(a) (b)

Figure 1. Typical AR system for (a) Face and emotion detection (b) Battlefield Environment Detection

Augment Reality (AR) systems process humongous amount data in real time (e.g., a typical AR system for human face and emotion and battlefield environment detection is shown in Fig.1). According to [1], without moving the head, our eyes can shift across a field of view of 150° horizontally and 120° vertically within less than 100 milliseconds. Add head and body rotation for 360° horizontal and 180° vertical for a total of more than 2.5G pixels. In addition, our eye can receive 720 million pixels for each of 2 eyes, at 36 bits per pixel for full color and 60 frames per second which is a total of 3.1T bits. That is a 5.2 Gbps of network throughput even if future compression could reach a factor of 600. Therefore, we need a new network architecture, which can multicast and cache AR video feeds close to consumers and then performs advanced video processing to construct individualized views.

Research Problem

QoE-aware Collaborative AR system focuses on a cross layer optimization problem. On application level, each AR device adopts the transmission strategy that maximizes its own utility (accuracy) based on local processing capabilities. V_j is the measurable QoE metrics, d_j is the influence factor, U_i is the normalized delay influence (1: no delay, 0: infinite delay).

$$\max_{0\le j<\infty} V_j d_j \sum_{0\le i<\infty} U_i\,, \qquad s.t \sum_{0\le j<\infty} V_j d_j \le 1, U_i \in [0,1]$$

On network layer, resource allocation algorithms that maximize the spectrum utilization efficiency and total utility among all n nodes, such as

$$\max_{\{X_n \ge 0, 1\le n\le N\}} \sum_n U_n(X_n) \qquad s.t. X_n \le X_{max}$$

where, $U_n(X_n)$ is the utility function based on the resource allocated to user n, X_n.

Reference

[1] Ejder Bastug, Mehdi Bennis, Muriel Medard, and M'erouane Debbah. 2016. Towards Interconnected Virtual Reality: Opportunities, Challenges and Enablers. CoRR abs/1611.05356 (2016). http://arxiv.org/abs/1611.05356
[2] Tiffany Yu-Han Chen, Lenin Ravindranath, Shuo Deng, Paramvir Bahl, and Hari Balakrishnan. 2015. Glimpse: Continuous, real-time object recognition on mobile devices. In Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems (Sensys). ACM, 155–168.

System Architecture

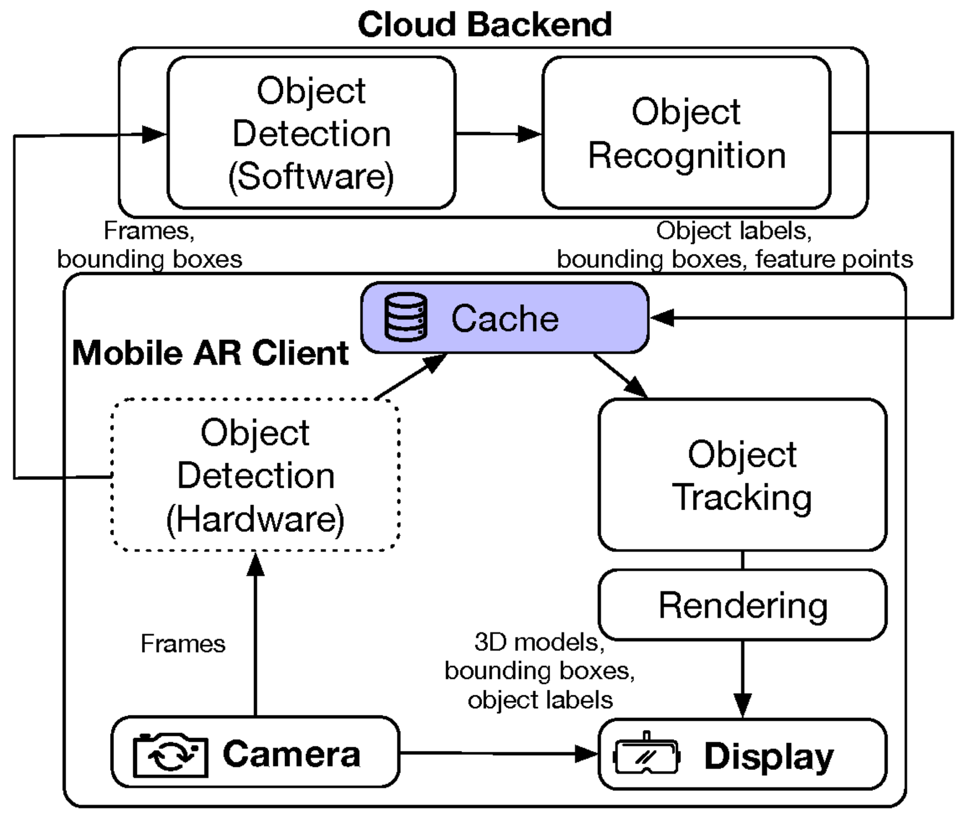


Figure 2. Architecture for common mobile AR applications

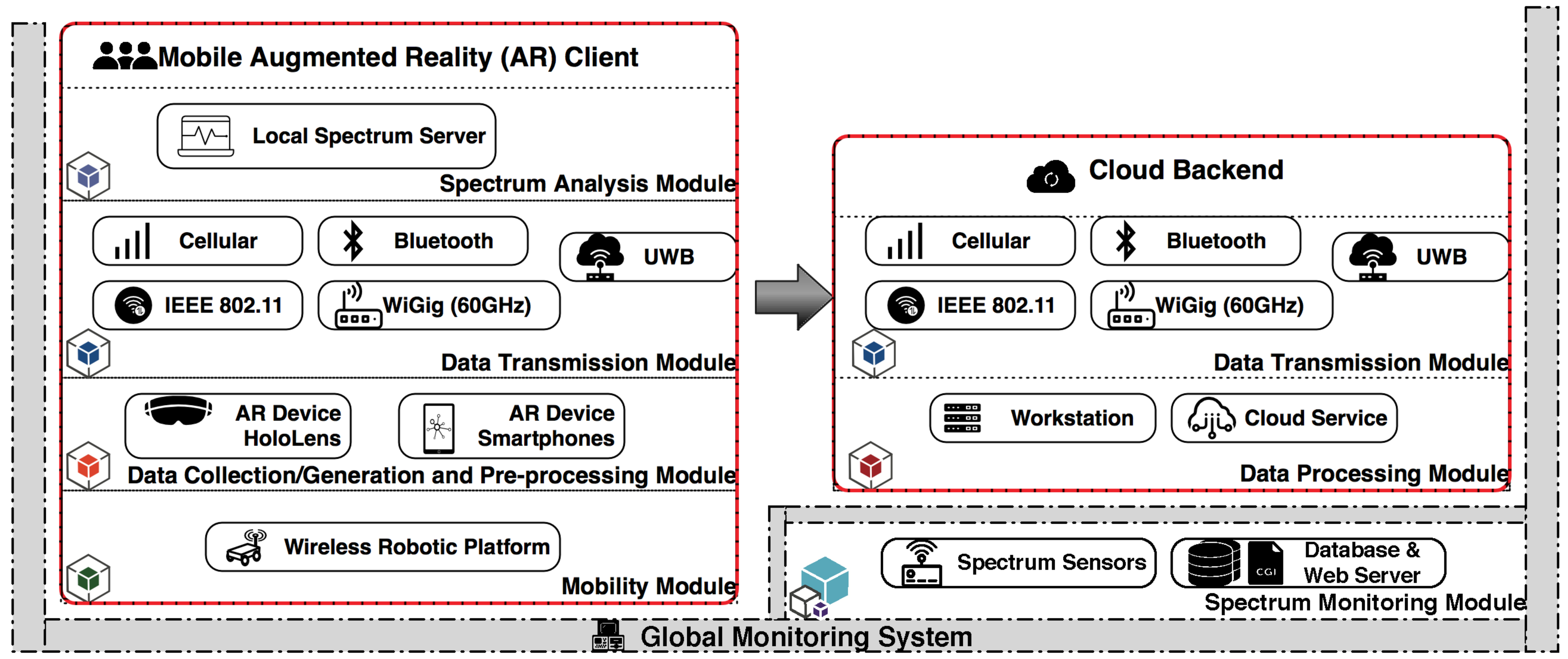


Figure 3. The system architecture of Q-CARS

Our study is conducted in a sample QoE-aware Collaborative AR system (called **Q-CARS** as shown in Fig.3). The desired research infrastructure consists of three components based on a typical client-cloud structure. The first component is the **mobile AR client**, which allows us to investigate the challenges in support of QoE, design mechanisms for AR-based wireless data generation, data pre-processing, and data transmission. This component is composed of four modules: 1) *data generation*, 2) *data transmission*, 3) *mobility control*, and 4) *spectrum analysis*.The second component is the **cloud backend**. The major function of this component is, for different domain-specific AR applications (e.g. Battlefield AR System), to process the received data from all mobile AR clients and to perform the detection, feature extraction, recognition/labeling, and other advanced computation operations that are expensive in the local processing. It is also equipped with data transmission module.The third component is a **global monitoring system** with a web-portal which continually monitor and analyze the whole system performance that includes the real-time packet drop rate, throughput, and performance of the mobile AR clients (e.g., trackability).

Preliminary Results and Conclusion

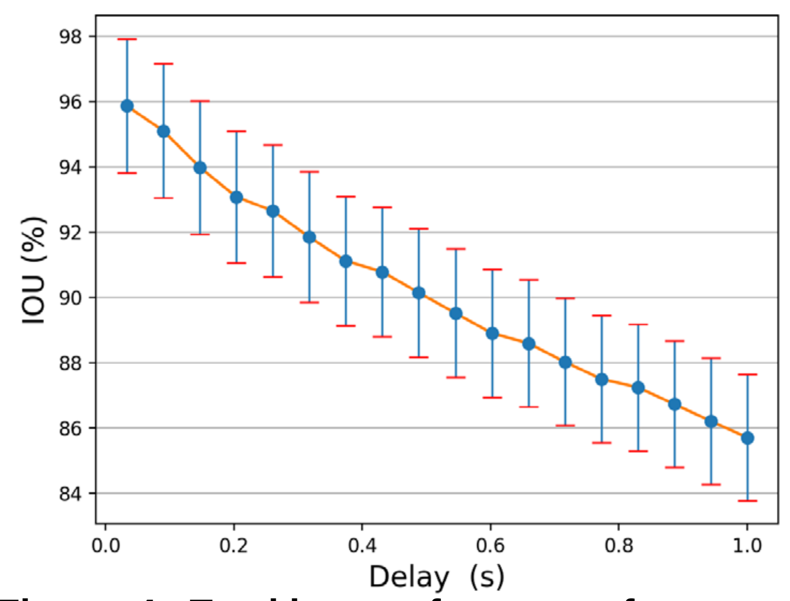
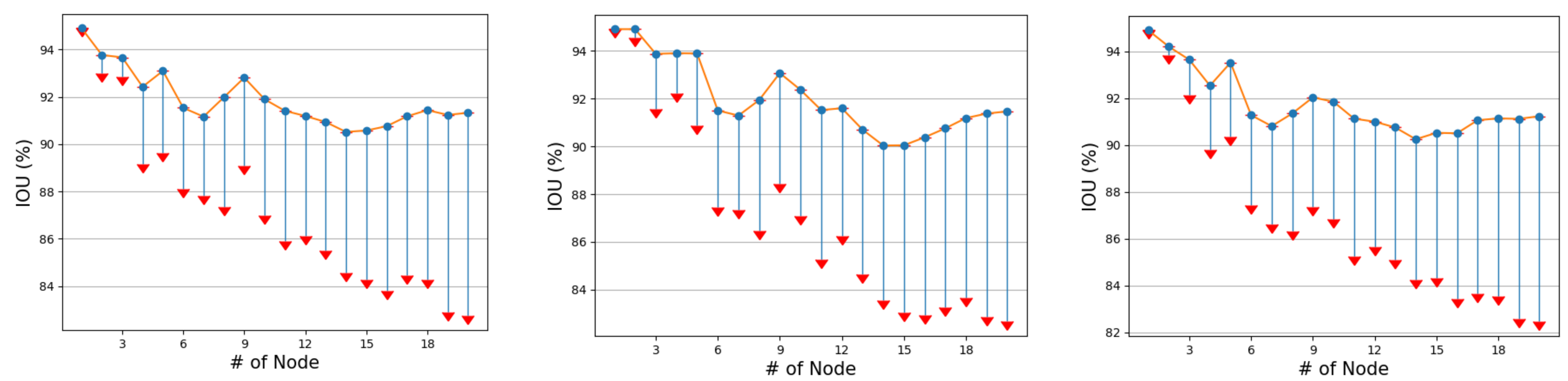


Figure 4. Tracking performance for a mobile AR application under different network conditions



(a) First Come First Serve (FCFS) (b) Smallest First (c) Earliest First

Figure 5. Tracking performance for multiple mobile AR clients under different scheduling algorithm.

We first conduct an experiment to determine the desired QoE by judging the trackability of our mobile AR system. We use intersection over union (IOU) [2] as the measure. For certain object ***i*** the IOU is calculated based on the intersection area between ground truth bounding box and the predicted bounding box divided by the union area of these two boxes.
Based on our preliminary results (shown in Fig. 4), we observe that the tracking performance of AR application decreases when the network delay increases. We further conduct an experiment to test the tracking performance for multiple mobile AR clients under different scheduling algorithm. As shown in Fig. 5, the overall tracking performance decrease when the number of node increase, this is due to the wireless interference between each AR clients. Among these three scheduling algorithms, the smallest first algorithm provides a better result when the total number of the AR clients is less than 6.

Future Research

There are two future research directions. First, we will focus on the cross layer optimization which generate best strategies for individual AR devices and algorithms that optimizes network resource allocation, while considering malicious and greedy users.
Second, we will deploy the real system that allows us to measure the real impact from wireless network to AR systems in various scenarios (indoor, outdoor) and verify our proposed cross layer optimization algorithms.