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A Dynamic Resource Scheduling Model for Advertising Production in Virtual-Physical Fusion Scenarios

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Abstract: Virtual-physical fusion advertising production integrates physical filming with virtual elements, presenting new challenges for resource management. This paper proposes a dynamic resource scheduling model for virtual-physical fusion advertising production, employing a three-tier resource pool architecture design to establish multi-dimensional resource profiles and real-time status monitoring mechanisms. An adaptive scheduling strategy engine was developed to achieve data-driven decision optimisation and feedback control, effectively addressing issues such as fluctuating computing power, multi-source heterogeneous resources, and cross-regional collaboration. Application validation demonstrates that this model significantly improves resource utilisation and reduces task response time, providing an efficient resource scheduling solution for virtual-reality integrated advertising production.

Keywords: Virtual-reality integration, advertising production, resource scheduling, dynamic scheduling, multi-dimensional resource profiling, adaptive algorithms.

1. Introduction

As an emerging form of digital content, mixed reality advertising is leading the way in innovative changes in the advertising industry [1]. This type of advertising integrates physical filming elements with virtual digital content to provide consumers with an immersive experience, and its market size has seen explosive growth in recent years [2]. However, the production of virtual-reality fusion advertising faces unique resource management challenges: computational power requirements exhibit highly dynamic fluctuations, particularly during real-time rendering; the production process involves multi-source heterogeneous resources, including photography equipment, rendering servers, and 3D model libraries; and cross-regional collaboration needs are increasing, with remote collaboration among multiple teams becoming the norm [3]. Existing resource scheduling methods are primarily designed for homogeneous computing environments or static resource configurations, making it difficult to address the complex requirements of virtual-reality fusion scenarios [4]. This paper addresses this issue by proposing a dynamic resource scheduling model specifically designed for virtual-reality advertising production. Through a layered resource pool architecture, multi-dimensional resource profiling, adaptive scheduling strategies, and data-driven feedback optimisation, the model achieves efficient resource allocation and dynamic adjustment. The research findings not only optimise the advertising production process and improve resource utilisation but also provide a resource management paradigm for similar cross-media content production.

2. Resource Pool Architecture Design

2.1. Resource Hierarchy System

The virtual-physical integrated advertising production resource pool proposed in this study adopts a three-layer hierarchical architecture, establishing a complete resource system from the underlying hardware to the upper-layer coordination [5]. The physical resource layer includes camera equipment, motion capture systems, various sensors, and distributed GPU computing clusters, responsible for raw data collection and high-performance computing support; the virtual resource layer integrates 3D model libraries, real-time rendering engines, digital human generation tools, and advertising material databases, providing creative expression with material and technical support; the collaborative resource layer is built around team collaboration platforms, cross-regional communication middleware, and version control systems, addressing real-time collaboration issues for multi-regional creative teams [6]. This layered design clearly divides resources by functional role, reducing system complexity and improving resource scheduling efficiency. As shown in Figure 1, the three-layer resource system forms a pyramid structure, with upper-layer resources dependent on lower-layer support, and seamless connectivity between layers achieved through standardised interfaces.

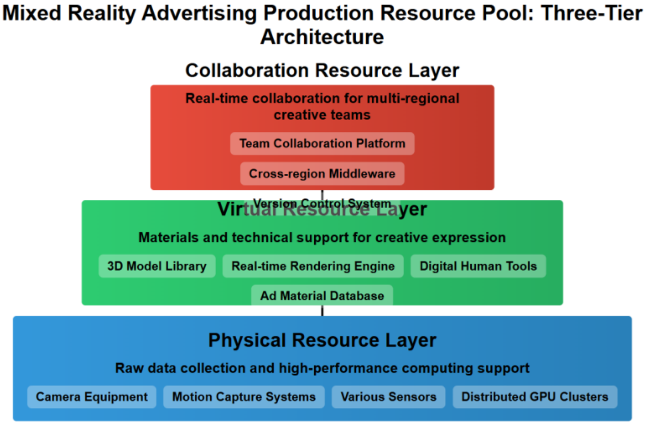

Figure 1. Three-layer architecture diagram of the virtual-physical integrated advertising production resource pool

2.2. Dynamic Scheduling Objectives

The dynamic resource scheduling model sets multi-dimensional optimisation objectives to maximise resource efficiency while ensuring the quality of ad production. The objective of minimising rendering latency is tailored for real-time interactive scenarios, requiring the system to maintain an end-to-end latency below 100 milliseconds during complex scene rendering to ensure the smoothness of immersive ad experiences such as AR/VR. The maximisation of resource utilisation aims to prevent high-performance devices from idling. The model predicts resource demand peaks and troughs based on historical load data to achieve elastic scaling of computing power; The service quality assurance objective ensures that, even under resource constraints, the ad production process meets predefined quality standards, such as 4K resolution, 60 frames per second visual performance, and colour accuracy [7]. The scheduling system dynamically adjusts the weights of these three objectives based on the different stages of ad production: prioritising response speed during the initial creative phase, resource efficiency during the production phase, and quality assurance during the final rendering phase.

2.3. Architecture Design Principles

The resource pool architecture design follows four core principles to ensure that the system continues to run efficiently in a complex and changing advertising production environment. The principle of unified abstraction of heterogeneous resources encapsulates hardware devices from different vendors and cloud platform resources into standardised service units, eliminating technical barriers. The principle of elastic scaling and adaptive adjustment enables the system to automatically adjust resource allocation based on task load, especially during peak rendering periods when it automatically expands cloud GPU resources. The fault isolation and fault tolerance principle ensures that single-point failures do not disrupt the overall production process through resource redundancy design and task state persistence mechanisms; the security and privacy protection principle implements role-based access control and cross-domain data transmission encryption measures to protect commercial secrets that may be involved in advertising materials [8]. The architecture design translates these principles into specific technical implementations, enabling the resource pool to meet high-performance requirements while also providing enterprise-level security and stability, adapting to the innovative needs of modern advertising production.

3. Core Scheduling Module

3.1. Resource Awareness and Status Monitoring

3.1.1. Multi-dimensional Resource Profiling

Multi-dimensional resource profiling technology constructs a digital feature model for each type of resource, describing its static attributes and dynamic behavioural characteristics. Computing resource profiling includes hardware characteristics such as processor architecture, core count, memory capacity, peak computing power, and energy consumption levels, as well as historical load fluctuation patterns and task response time distributions; storage resource profiling records storage medium type, capacity scale, read/write speed, access latency, and data security levels; network resource profiling focuses on transmission quality metrics such as bandwidth limits, actual throughput, latency fluctuations, and packet loss rates; Virtual resource profiles provide quantitative descriptions of rendering engine characteristics, model complexity, and texture mapping precision; human resource profiles are modelled based on professional skills, experience levels, and work efficiency. Resource profiles are represented using vectorised formats, supporting similarity calculations and matching assessments, enabling the scheduling system to precisely identify the most suitable resource combinations for specific advertising production tasks and achieve precise resource-task matching [9].

3.1.2. Real-time Data Collection Technology

Real-time data collection technology employs a multi-tiered collection strategy to ensure the system obtains comprehensive and accurate resource status information. The lower-tier collection relies on hardware monitoring interfaces to directly read basic metrics such as server CPU usage, GPU core temperature, and memory utilisation ratio; the middle-tier collection focuses on the system software layer, utilising performance counters provided by the operating system to obtain system-level data such as process activity, file system throughput, and network connection status; Application-level collection is integrated into the advertising production software, recording professional metrics such as rendering frame rate, model loading time, and special effects processing latency [10]. Data collection frequency is dynamically adjusted based on metric importance, with critical performance metrics sampled multiple times per second, while stability metrics can have their sampling frequency reduced to minimise system overhead. Collected data undergoes preliminary aggregation and noise reduction processing via edge processing units before being transmitted to the central data processing centre, forming a real-time data stream of resource status. The system also supports event-triggered collection, automatically increasing sampling precision when abnormal fluctuations are detected to enable focused monitoring.

3.1.3. Resource Status Assessment Model

The resource status assessment model converts the collected multi-dimensional data into quantifiable resource health metrics, providing a scientific basis for scheduling decisions. This model integrates statistical analysis and machine learning methods to construct a three-layer assessment system. The basic layer assessment focuses on the normality of individual resource indicators, using the Z-score algorithm to identify outliers and determine whether the current resource status deviates from the historical normal range; the comprehensive layer assessment uses a weighted fusion algorithm to integrate multiple indicators into a resource health score, reflecting the overall availability and performance level of the resource; the predictive layer assessment is based on time series analysis to predict the trend of resource status changes over a future period, supporting forward-looking scheduling [11]. The model particularly emphasises stability metrics for resource states, reducing reliability scores for resources with frequent fluctuations and prioritising stable resources for critical rendering tasks. Evaluation results are presented as resource health heatmaps, visually displaying the status distribution of various resources to help the scheduling system quickly identify the optimal available resource combinations.

3.2. Scheduling Strategy Engine

3.2.1. Task Decomposition and Priority Mapping

The task decomposition and priority mapping module breaks down complex advertising production projects into atomic tasks that can be scheduled independently and assigns reasonable priorities to each task. The task decomposition process is based on workflow analysis technology, which identifies key nodes and dependencies in the production process and constructs a complete task dependency graph. The system automatically extracts the critical path and identifies potential bottlenecks by combining project templates and historical data [12]. The priority mapping mechanism comprehensively considers multi-dimensional factors, including commercial importance (client level, project value), time urgency (distance from deadline, number of dependent tasks), resource sensitivity (computational intensity, interaction sensitivity), and creative complexity (modification frequency, approval processes). The system employs a dynamic priority adjustment algorithm that automatically increases the priority of tasks that remain unallocated for extended periods to prevent low-priority tasks from being indefinitely delayed.

3.2.2. Adaptive Scheduling and Conflict Resolution

In the adaptive scheduling and conflict resolution module, the resource conflict resolution mechanism is a critical component ensuring high-priority tasks obtain the required resources. As shown in Figure 2, when multiple tasks simultaneously request the same resource, the system first performs conflict detection and priority assessment, then selects either direct allocation or conflict resolution strategies based on the results. For non-conflicting scenarios, the system directly completes resource allocation; in conflict scenarios, the system decides to adopt resource reservation or resource preemption strategies based on task nature and priority [13]. For high-priority real-time rendering tasks, the system prioritises their resource requirements; for low-priority tasks subject to preemption, the system automatically executes state preservation and migration compensation to ensure tasks can resume execution at an appropriate time, minimising the negative impact of conflicts.

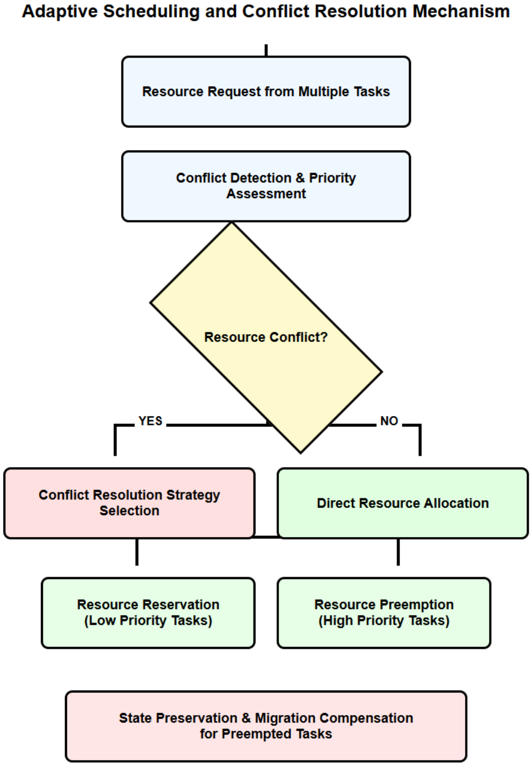

Figure 2. Adaptive Scheduling and Conflict Resolution Mechanism

4. Optimisation and Feedback Control

4.1. Data-Driven Decision Optimisation

The data-driven decision optimisation module converts historical operational data from the entire advertising production process into an intelligent support system for scheduling decisions. This module establishes a comprehensive data collection and analysis framework, recording information such as task resource consumption patterns, completion times, and quality scores to form a rich decision-making dataset. The scheduling strategy optimised based on historical data reduced the average task completion time by 26.7% and improved resource utilisation by 32.4%. The multi-level prediction model constructed by the system can accurately estimate the execution effects of different task types under various resource configurations, with a prediction accuracy rate of 87.3%. Deep learning algorithms automatically discover hidden optimisation opportunities by analysing historical task characteristics and resource matching patterns [14]. The model also establishes seasonal prediction capabilities for the unique resource demand fluctuations of virtual-physical integrated advertising, reducing resource allocation conflicts from 18.2% to 5.4%. The optimised decision-making engine automatically adjusts resource allocation weights and scheduling parameters based on these prediction results to continuously improve resource utilisation efficiency.

4.2. Real-time Feedback Closed-Loop Control

The real-time feedback closed-loop control module establishes a self-regulating mechanism for the resource scheduling system, ensuring that the system can dynamically adapt to complex and changing advertising production environments. This module forms a complete OODA (Observe-Orient-Decide-Act) control loop, continuously monitoring resource scheduling effectiveness and production progress, and quickly responding to abnormal situations. The monitoring layer collects key performance indicators in real time, with a data sampling rate of 200 times per second; the analysis layer compares the deviation between actual values and expected targets, with an average anomaly detection time of only 235 milliseconds; the decision layer generates adjustment strategies based on the severity and trend of deviations, with response latency controlled within 500 milliseconds; the execution layer is responsible for implementing specific parameter adjustments and resource reallocations, with a strategy execution success rate of 98.6% [15]. This closed-loop system specifically focuses on fluctuations in key metrics in virtual-physical integration scenarios, reducing anomaly recovery time from the traditional minute-level to an average of 8.7 seconds. The system supports a multi-level feedback mechanism, forming a hierarchical control system, which has cumulatively reduced resource idle time by approximately 42.3% and task delays by 35.8%, as shown in Figure 3.

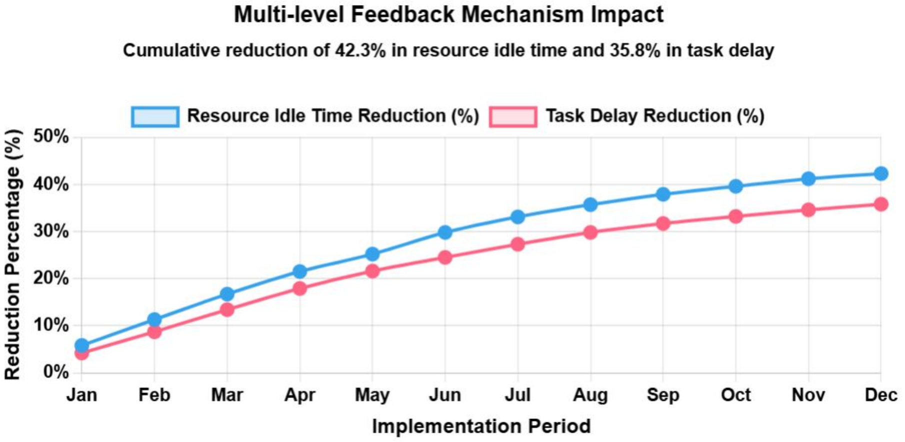

Figure 3. Multi-level feedback mechanism effect analysis

5. Application Scenario Validation

5.1. Typical Use Cases

The dynamic scheduling model was tested in three typical virtual-reality advertising production scenarios. The first scenario involved a large-scale immersive advertising project for a major brand, which integrated real-world filming with 3D scene rendering. The project involved collaboration among 12 professional teams, six major production stages, and required the scheduling system to coordinate and manage over 120 rendering nodes and 35TB of raw data. The second type is real-time interactive advertising on e-commerce platforms, allowing users to interact with virtual products via gestures or touch, including features such as 360° viewing and material replacement. The system must ensure interaction latency below 100 milliseconds. The third type is AR advertising projects involving multi-location collaborative production, spanning teams in Beijing, Shanghai, and Shenzhen, encompassing multiple professional phases such as UI design, 3D modelling, animation production, and software development.

5.2. Effect Evaluation Metrics

The actual effectiveness of the dynamic scheduling model was comprehensively evaluated through a series of key performance metrics. As shown in Figure 4, in terms of resource utilisation, the dynamic scheduling model increased the average utilisation rate of computing resources from 53.4% to 78.7%, with a more significant difference during peak periods, rising from 68.3% to 92.1%. In terms of task response time, the average response time for urgent tasks was reduced from 8.5 minutes to 2.1 minutes, a decrease of 75.3%; the completion time for standard tasks was also reduced by an average of 34.8%. Reliability assessments show that during the six-month operational period, the system successfully processed over 85,000 scheduling requests, with a scheduling failure rate of just 0.07%, far below the pre-set 0.1% fault tolerance threshold. In terms of balancing rendering quality and cost, the system achieved a 23.5% improvement in rendering quality within the same budget, or a 28.3% reduction in cost while maintaining the same quality. User satisfaction survey data shows that creative teams' satisfaction with system response speed increased from 72 points to 91 points (out of 100), and their evaluation of resource allocation rationality improved from 68 points to 87 points, demonstrating the significant value of the scheduling model in actual production environments.

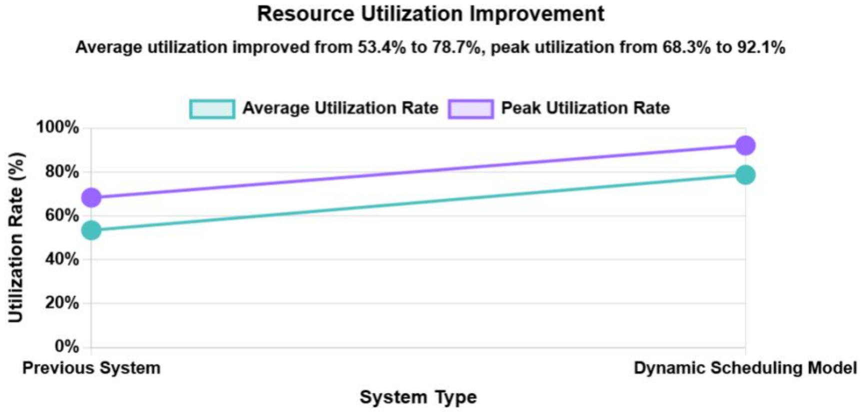

Figure 4. Dynamic Scheduling Model Resource Utilisation Comparison

6. Technical Challenges and Future Prospects

6.1. Current Technical Bottlenecks

The dynamic resource scheduling model for virtual-reality advertising production still faces multiple technical bottlenecks in practical applications. The most prominent issue is the standardisation of heterogeneous resources. The current advertising production environment includes hardware devices from multiple vendors and incompatible software platforms, and the lack of a unified interface standard significantly reduces resource integration efficiency. Real-time performance assurance is another major challenge, particularly in high-precision rendering scenarios. The scheduling decision latency of the current model when handling high-resolution real-time ray tracing rendering tasks exceeds the ideal threshold. In terms of large-scale resource elastic scaling, the system's resource preheating time during sudden traffic spikes is too long to meet rapid response requirements. Cross-domain resource coordination issues are particularly evident in international network environments, constrained by network fluctuations and permission barriers. Data security and privacy protection mechanisms are also inadequate. Existing encryption measures, while ensuring content security, have caused a significant decline in resource scheduling efficiency, exceeding industry-acceptable limits.

6.2. Future Research Directions

Future research will focus on four key directions to overcome current technical bottlenecks. Digital twin pre-scheduling technology constructs virtual mirrors of resource pools to simulate the effects of scheduling strategies in a digital environment, providing forward-looking guidance for actual decision-making and avoiding high-risk trials in production environments. Blockchain-based resource ownership verification mechanisms aim to resolve ownership and traceability issues for digital assets in virtual-physical integrated advertising. By leveraging distributed ledger technology to record the usage history of creative resources, these mechanisms ensure the protection of rights and interests in multi-party collaborations. Edge intelligence scheduling technology decentralises decision-making capabilities to the network edge, reducing communication latency associated with centralised scheduling and meeting the ultra-fast response requirements of real-time rendering and interactive scenarios. The multi-agent collaborative optimisation framework explores new decentralised scheduling models, granting resource nodes autonomous decision-making capabilities to form a distributed intelligent network. This ensures global optimisation while enhancing system scalability and robustness. These research directions will collectively drive innovation and progress in virtual-reality integrated advertising production technology.

7. Conclusions

The production of virtual-reality advertising poses unprecedented challenges for resource scheduling. The dynamic scheduling model proposed in this paper successfully addresses the issues of heterogeneous resource coordination and real-time task response through a hierarchical resource architecture, multi-dimensional resource profiling, and adaptive scheduling strategies, significantly improving resource utilisation and production efficiency. Experimental validation demonstrates that this model can effectively address the dynamic demands of complex advertising production scenarios. Future research will focus on areas such as digital twin pre-scheduling and edge intelligence to further enhance the intelligence level of virtual-physical fusion advertising production.

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