

## *Retraction*

# **Retracted: ARToolKit Target Tracking and Animation Fusion Technology Based on Edge Computing and Augmented Reality**

### **Wireless Communications and Mobile Computing**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] K. Liu, T. Guo, and Y. Fu, "ARToolKit Target Tracking and Animation Fusion Technology Based on Edge Computing and Augmented Reality," *Wireless Communications and Mobile Computing*, vol. 2023, Article ID 4121255, 15 pages, 2023.

## Research Article

# ARToolKit Target Tracking and Animation Fusion Technology Based on Edge Computing and Augmented Reality

Kun Liu,<sup>1</sup> Tingting Guo ,<sup>2</sup> and Yao Fu<sup>3</sup>

<sup>1</sup>Faculty of Art Design, Guangdong Baiyun University, Guangzhou, 510450 Guangdong, China

<sup>2</sup>Information Department, Guangdong Teachers College of Foreign Language and Arts, Guangzhou, 510640 Guangdong, China

<sup>3</sup>Arts Design Department, Guangdong Teachers College of Foreign Language and Arts, Guangzhou, 510640 Guangdong, China

Correspondence should be addressed to Tingting Guo; guott@gtcfla.edu.cn

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Since the beginning of the 21st century, computer network technology has been developing at a rapid speed. Many things that people thought were remote or even impossible 10 years ago can now become a reality, such as AR. AR is augmented reality. After simulating computer-generated text, image, 3D models, music, video, and other virtual information and applied to the real world, the two kinds of information complement each other, so as to achieve the “enhancement” of the real world. AR is augmented reality, a new field that is currently emerging. Using AR technology can add a realistic and virtual atmosphere to the real environment, giving users a better visual experience. Edge computing is a more efficient algorithm based on cloud computing. Traditional cloud computing, which requires all terminal devices to go from the cloud to the edge, consumes more energy and time, while using edge computing is more efficient. Applying edge computing to AR can render videos and pictures in real time, giving users a better experience. This paper is aimed at studying the ARToolKit target tracking and animation fusion technology based on edge computing and augmented reality and using this technology to propose and design an AR computing edge model. And compared with the traditional AR technology, the final experimental results show that the use of ARToolKit target tracking and animation fusion technology based on edge computing and augmented reality can reduce the minimum delay time by 1/3 compared with traditional cloud computing. The signal-to-noise ratio of the fused animation effect is significantly increased. Compared with the traditional gray value fusion, it only needs 1/2 of the number of calculations to achieve the same fusion effect.

## 1. Introduction

**1.1. Background.** With the rapid development of electronic information and communication technologies such as the Internet of Things, 5G, blockchain, the Internet, and sensors, the growth of various types of data is advancing by leaps and bounds. This is a trend, and the demand for computing power and speed for large amounts of data is also increasing. The service model of the existing cloud computing model has a series of problems such as large network delay, privacy security, and high cost. The low-latency calculation model is particularly important in decision-making intelligent events, for example, in industrial production, operation and other scenarios, real-time response to accidents, failures, and

emergencies. Data transmission costs are more sensitive in network data capture scenarios, so there is an urgent need to develop high-quality AR products to meet people's greater needs. At present, the idea of using high-quality products combining edge computing and AR is emerging, and breakthroughs in development technology are the key to the problem.

**1.2. Significance.** Edge computing combines the edge and storage devices close to users with cloud computing to provide solutions with low latency, high processing, and data collection, processing, and analysis. As a software development tool widely used in the AR field, ARToolKit uses target tracking technology to predict and track the movement

of markers in combination with ARToolKit to improve the real-time performance of the target tracking algorithm. Use animation fusion technology to realize the fusion of virtual scenes and objects with real scenes to produce the envisaged visual effects. Aiming at the characteristics of the above-mentioned technologies, the realization of ARToolKit's target tracking and animation fusion technology based on edge computing and augmented reality will be a major innovation.

*1.3. Related Work.* In recent years, edge computing is developing rapidly with a new vision. The industry's investment and research interest in edge computing has increased significantly. This new technology is expected to provide responsive cloud services and the Internet of Things for mobile computing, implement scalability and privacy policies, and shield dynamic cloud interruptions. Nowadays, more and more scholars are studying this new technology. Shi introduced several case studies of offloading edge computing from the cloud to smart homes and cities, as well as the concept of using the edge to implement edge computing, and demonstrated the advantages of using it to process data [1]. The accompanying content that Satyanarayanan uses edge computing to post to the YouTube network includes a video playlist that demonstrates the concept of the three tasks implemented by the verification. However, the demonstration experiment was too simple and did not consider many factors such as environmental differences [2]. The same rise of new mobile edge computing (MEC, formerly edge computing before 5G). With the rise of new mobile edge computing (MEC) technology, Taleb T-Analysis uses common transmission equipment that reaches the vicinity of MEC service equipment and can publish general-purpose calculations during high-density work installations, effective use of wholesale and demand dynamic management radio calculation sources, time-varying calculation demand radio calculation sources. In addition, Taleb T-Analysis has also completed third-party activation support for MEC reference architecture, main and subscenarios, applications, development business, content provisioning business, and multitenancy. His research on the theory of large MEC was also carried out simultaneously with other experiments [3]. Mao has developed an online joint radio and computing resource management algorithm for multi-user MEC systems. The goal is to minimize the long-term average weighted sum power stability constraint of the mobile device and the MEC server in the case of the task buffer. In addition, Mao proposed a delay improvement mechanism to reduce execution delay. The rigorous performance analysis of the proposed algorithm and its delay improvement shows that the weight, power consumption, and execution delay follow the trade-offs as control parameters. It provides simulation results to verify the theoretical analysis and prove the influence of various parameters. The research algorithm is of course very effective. Nowadays, more and more scholars are studying and discussing MEC, but the research has not been commercialized [4]. In order to further reduce the offloading calculation delay and transmission cost, Ke proposed a cloud-based mobile edge com-

puting (MEC) offloading framework for vehicle networks. Tasks are adaptively offloaded to the MEC server through direct upload or predictive relay transmission. The results show that the proposed scheme significantly reduces the calculation cost and improves the task transmission efficiency. Facts have proved that edge computing can reduce computing costs and improve transmission efficiency, but more experimental demonstrations are needed to obtain more accurate results [5]. He uses the edge computing environment to integrate the deep learning of the Internet of Things, but the nodes are not perfect and the processing capacity is limited, so another offloading strategy is designed. Using edge computing to test the performance of multiple deep learning tasks, the performance of IoT deep learning applications is improved through edge computing. Due to the limitations of existing nodes, the edge computing method is not pure and cannot intuitively illustrate the performance advantages of edge computing [6]. Marker-based tracking is currently the most commonly used method for developing AR applications. However, due to the limited use of site markers, this method is not suitable for some complex outdoor environments, such as prehistoric rock painting sites. Therefore, natural feature tracking methods should be used, and various libraries can be used to develop AR applications based on tracking natural features. Blanco-Pons conducted a comparative study on the Vuforia and ARToolKit libraries to analyze the factors that ultimately affect the user experience in indoor and outdoor environments, such as distance, occlusion, and lighting conditions. The analysis of Blanco-Pons confirmed that Vuforia may be better than ARToolKit indoors, but it does not work well outdoors. Since ARToolKit can be used to develop AR applications in complex outdoor environments such as rock painting sites, ARToolKit's compatibility with multiple complex environments makes it more practical [7].

*1.4. Innovation.* (1) Take advantage of the data acquisition advantages of edge computing with low latency and high processing capacity, which is energy-saving and efficient. (2) Use augmented reality ARToolKit library that can adapt to different environments, which is more practical. (3) Combining advanced target tracking technology, real-time tracking of static and dynamic targets is more real and accurate. (4) Combined with advanced animation fusion technology, it gives people a visually realistic and shocking beauty. (5) Carry out AR tests in different scenarios and use experimental results to demonstrate. (6) Compared with traditional AR products, the difference between the two can be more prominent.

## 2. AR New Target Tracking Algorithm under Edge Model

*2.1. Edge Computing.* Edge computing refers to the use of open platforms to integrate the core capabilities of networks, computing, storage, and applications closer to objects and data sources to provide nearby services. Applications start from the edge to generate faster network service responses and meet the industry's fundamental needs in real-time

business, application intelligence, security, and privacy protection. If cloud computing is the human brain, edge computing is the human nerve endings, which can receive data faster and more directly. Edge computing itself is just a method or mode to realize the computing technology required for the Internet of Things, intelligent manufacturing, etc. Strictly speaking, edge computing is computing that is close to the field application side. Its essence is relative to cloud computing. It can be seen from the computing paradigms of the two that the data computing on the edge side has suddenly become richer. Since Akamai and IBM cooperated in 2003, edge computing has been developed for more than 18 years. In order to better understand edge computing, Figure 1 intuitively compares traditional cloud computing with edge computing. It can be seen from Figure 1 that data consumers can retrieve data faster through edge computing, and data producers can also provide services for data more conveniently through edge computing. Because much of the control will be done locally on the device and not in the cloud, the processing will be done at the local edge computing layer. This greatly improves processing efficiency and reduces the load on the cloud. Due to being closer to the user, it can also provide users with a faster response and solve their needs at the edge. In this way, the amount of data through cloud computing is relatively reduced, and the pressure of cloud computing is naturally reduced [8]. Although these methods can complete the fusion of ARToolKit target tracking and animation to a certain extent, most of them are based on theoretical research with few practical applications, and the implementation cost is high and the efficiency is insufficient. Therefore, this paper uses edge computing and AR methods to solve this problem and improve.

**2.1.1. Edge Computing Model.** The AR application uses the camera and screen to superimpose the computer image on the actual image. This process includes video source, renderer, tracker, mapper, and object recognition functions. The first two parts are used for devices, and the last three parts are offloaded to the cloud edge. Edge computing offloading means that the user terminal (UE) offloads computing tasks to the MEC network, which mainly solves the shortcomings of equipment in terms of resource storage, computing performance, and energy efficiency. The unloading process is node discovery, program cutting, unloading decision, program transmission, execution calculation, calculation result end, and unloading decision. In order to further study the actual efficiency of edge computing, this paper constructs an edge computing model in AR scenarios. For the convenience of calculation, this model refers to the link where data consumers (users) search for data in the data cloud or cloud edge as the uplink, and the link that responds to users after cloud computing or edge computing is called the downlink [9].

Assuming that there are  $n$  users running AR applications in a certain area, set  $n = \{1, 2, \dots, n\}$ , the base station has a cloud server, equipped with a high amount of calculation, and can process data uploaded by users. The cloud server is connected to a single-antenna base station and uses split pairs to provide services for all users in the cell on a flat fre-

quency fading channel. The model assumes that the same AR application is running simultaneously with the input, output, and computing tasks related to the tracker, mapper, and object recognition component. At the same time, special consideration is given to the synergy in the transmission process [10]. Also, in the transmission during transmission, i.e., the up or down processes of transmission produce different data and models,  $x$  needs to be considered separately.

**2.1.2. Uplink Transmission.** If the number of users in the area is  $n \in N$ , then when the AR application is running, the data that needs to be processed, such as the input bits for object recognition, needs to be transmitted to the cloud server for calculation. Considering that each user has part of the same input bit, then this part of the user data in the area can be sent cooperatively, so as to avoid uploading multiple data [11]. This article describes this part  $B_s^u$  of the input bits that are the same as the shared input bits, and

$$B_s^u \leq \min_n \{B_n^u\}. \quad (1)$$

Each user  $n$  cooperates to send some shared input bits  $B_{s,n}^u$  and  $\sum_{n=1}^n B_{s,n}^u = B_s^u$ , and then, the input bits uploaded separately by each user  $n$  are

$$\Delta B_n^u = B_n^u - B_s^u. \quad (2)$$

**2.1.3. Downlink Transmission.** Certain output bits must be passed to all users. If the user is at the same coordinate location, the updated map is calculated with the output position of the mapper [12]. The model assumes that  $B_s^d \leq \min_n \{B_n^d\}$ , the output bits can be sent to all users in the cell in multicast mode. The “pair by group” communication mode between the hosts, that is, the hosts with the same group can accept all the data in this group, and the switches and routers in the network only copy and forward the required data to the demanders. And  $\Delta B_n^d = B_n^d - B_s^d$  must send bit  $n$  to each user in unicast mode.

**2.1.4. System Transmission Process**

**(1) Transmission Rate.** Assuming that the signal is in a normal and stable state during transmission, given that the signal increment and increment value between user  $n$  and the base station is  $\Delta a_n$ , the uplink data transmission rate calculation formula is as shown in

$$R_n^u(P_n^u) = B^u a_n \log \left( 1 + \frac{\Delta a_n P_n^u}{\delta_0 B^u a_n} \right). \quad (3)$$

In the formula,  $P_n^u$  is the transmission power of the facility with the number of users  $n$ ,  $B_n^u$  is the total number of transmission bits for the number of users  $n$ , let  $B^u$  be the total number of uplink transmission bits, then  $\sum_{n=1}^n B_n^u = B^u$ , and  $\delta_0$  is the interference density.

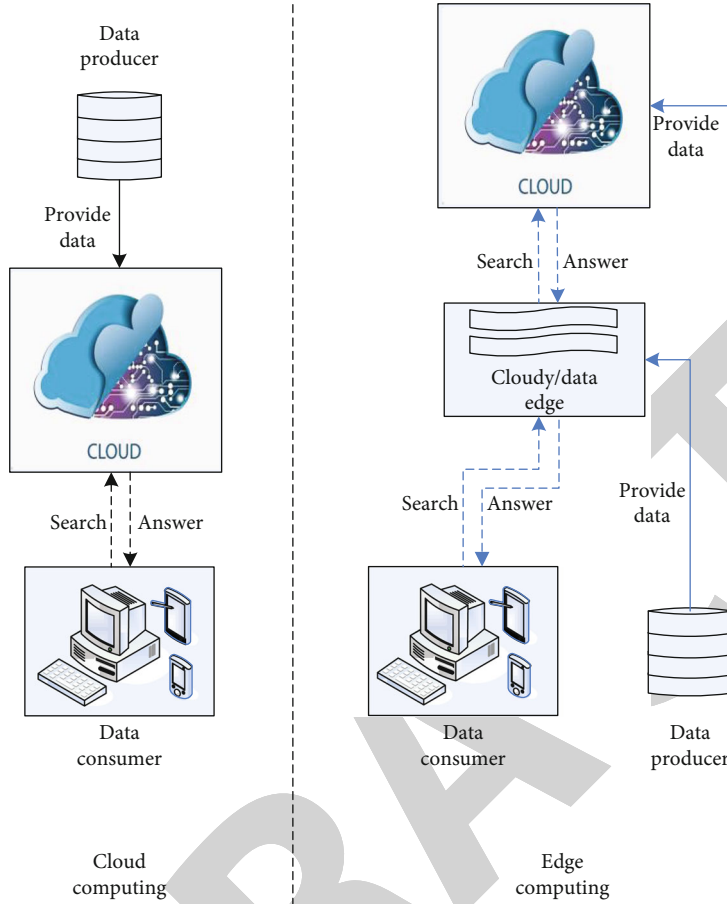


FIGURE 1: Cloud computing and edge computing.

For the shared output bit  $B_{s,n}^u$ , all users receive data in the form of multicast and then transmit data in the form of downlink multicast. The rate calculation formula is as shown in

$$R_{m,n}^d(P_m^d) = B^d \log \left( 1 + \frac{\Delta a_n P_m^d}{\delta_0 B^d} \right). \quad (4)$$

In the formula,  $P_m^d$  is the downlink multicast transmission power,  $B^d$  is the total downlink transmission bits, and  $\sum_{m=1}^n B_n^d = B^d$ .

For the output bit  $B_n^d$  that is sent to user  $n$  separately, the transmission is in the solo mode and then the downlink transmission data of solo; the rate calculation formula is as

$$R_n^d(P_n^d) = B^d a_n \log \left( 1 + \frac{\Delta a_n P_n^d}{\delta_0 B^d a_n} \right). \quad (5)$$

Among them,  $P_n^d$  is the downlink transmission power corresponding to user  $n$ .

(2) *Transmission and Processing Time.* User  $n$  uploads part of the shared input bit  $B_{s,n}^u$ ; the required time

$$T_s^u = \frac{B_{s,n}^u}{R_n^u(P_n^u)}. \quad (6)$$

The time required for user  $n$  to receive the multicast shared output bit  $B_s^d$

$$T_s^d = \frac{B_s^d}{R_{m,n}^d(P_m^d)}. \quad (7)$$

User  $n$  independently uploads the remaining number of bits  $\Delta B_n^u$ ; the time required

$$T_a = \frac{\Delta B_n^u}{R_n^u(P_n^u)}. \quad (8)$$

User  $n$  receives the number of unicast output bits  $\Delta B_n^d$ ; the required time

$$T_b = \frac{\Delta B_n^d}{R_n^d(P_n^d)}. \quad (9)$$



The processing time of the cloud server is set to  $T_c$ ; then, in the system, the delay time  $T$  required for user  $n$  to perform edge computing is

$$T = \max_n(T_s^u) + \max_n(T_s^d) + T_a + T_b + T_c. \quad (10)$$

(3) *Transmission Energy.* The energy consumption of user mobile edge computing lies in the transmission of uplink data and the reception of downlink data [13].

The energy generated by the uplink data transmission of user  $n$  is

$$E_n^u(B_{s,n}^u) = \frac{(B_{s,n}^u + \Delta B_n^u)}{R_n^u(P_n^u)}(P_n^u). \quad (11)$$

The energy generated by the downlink data transmission of user  $n$  is

$$E_n^d(P_n^d, P_m^d) = \left( \frac{\Delta B_n^d}{R_n^d(P_n^d)} + \frac{B_s^d}{R_{m,n}^d(P_m^d)} \right) e_n^d, \quad (12)$$

where  $e_n^d$  is the energy consumed by user  $n$  to capture downlink data per second.

Edge computing is a continuum, and the edge is the calculation between the paths from the data to the cloud computing center. Whether it is edge, cloud, or fog computing, it is just a way and mode for intelligent manufacturing and providing computing technologies such as the Internet of Things. Due to the different levels of edge node network bandwidth and computing capabilities, choosing a suitable edge node will significantly reduce the computing delay. In particular, certain infrastructures can be used as edge nodes accessed using handheld smart models. When transmitting data, first link to the nearest station and then access the main communication network; edge nodes in large networks can reduce latency. This way of using the existing infrastructure as an edge node increases the delay for supporting equipment to bypass the base station and directly access the backbone network. Screening more appropriate edge nodes to reduce computing power consumption and communication delay is a difficult problem that needs to be considered. In this process, it is necessary to consider the existing infrastructure, for example, how to combine edge nodes and edge computing technology, whether the new ecological environment has completely changed the type of existing infrastructure.

It has only been a few years since edge computing was officially proposed. In this explosive growth of innovative research, it is believed that this trend will continue. Therefore, edge computing will bring greater spillover effects, and the development of different fields and smart industries will upgrade and transform the entire industrial system [14].

## 2.2. ARToolKit Target Tracking Technology

2.2.1. *ARToolKit Coordinate System.* ARToolKit is mainly composed of AR module, video module, and GSILb module

function library. As mentioned earlier, the biggest advantage of ARToolKit is that AR programs can be used in complex environments. Target tracking detection is mainly carried out by establishing a coordinate system, which mainly includes a visual coordinate system, a screen coordinate system, a camera coordinate system, and a reference object coordinate system. Figure 2 is the coordinate system used in the development of ARToolKit. The concept and importance of each coordinate system will not be discussed in detail here [15].

2.2.2. *Visual Tracking Recognition System.* Of course, with the coordinate system, a visual tracking recognition system is also needed. Its function is to calculate the space coordinates and convert them into parameters, calculate the coordinate positions of the reference objects in the real space and perform real-time tracking and positioning, and display these objects in the correct image position in real time. The content of the visual registration system should include logo design, logo tracking and collection, and identification signs [16].

(1) *The Design of the Mark.* The design of the mark should be easy to identify, and the identification methods should be diversified, that is, to set multiple nodes or feature points that are easy to identify. The identification method can be based on the shape, size, color, outline, and feature points of the marker.

(2) *Trace Collection of Signs.* Tracking and acquisition is the most important and critical step. There are many current target tracking and acquisition methods. Figure 3 shows the flow of the classic target tracking algorithm. The algorithm is relatively simple and has many limitations. In order to make the algorithm more perfect, this paper designs an improved target tracking algorithm and compares it with the traditional target tracking algorithm to verify the actual utility of the algorithm [17].

It can be seen from the flow of the improved target tracking algorithm in Figure 4 that the algorithm changes each element on the stack from a pixel to a structure. The stack can only be input and output at one end, and it consists of a fixed stack bottom and a floating stack top. It can be understood as a pointer to the top element of the stack. Compared with the traditional algorithm, the stack space is significantly reduced, the program efficiency is improved, the row of the scan line where the current search element is located is filled, and the upper and lower rows are filled. Part of the scan line does not need to be scanned multiple times, which further improves the scanning efficiency. The approach converts each pixel on the stack into a structure, saving stack space, increasing program performance, and filling the scanline row where the current search element is situated. In order to express the practicality of the algorithm more intuitively, this paper analyzes and compares the performance of the algorithm. Detailed information can be found in the following experimental analysis [18].

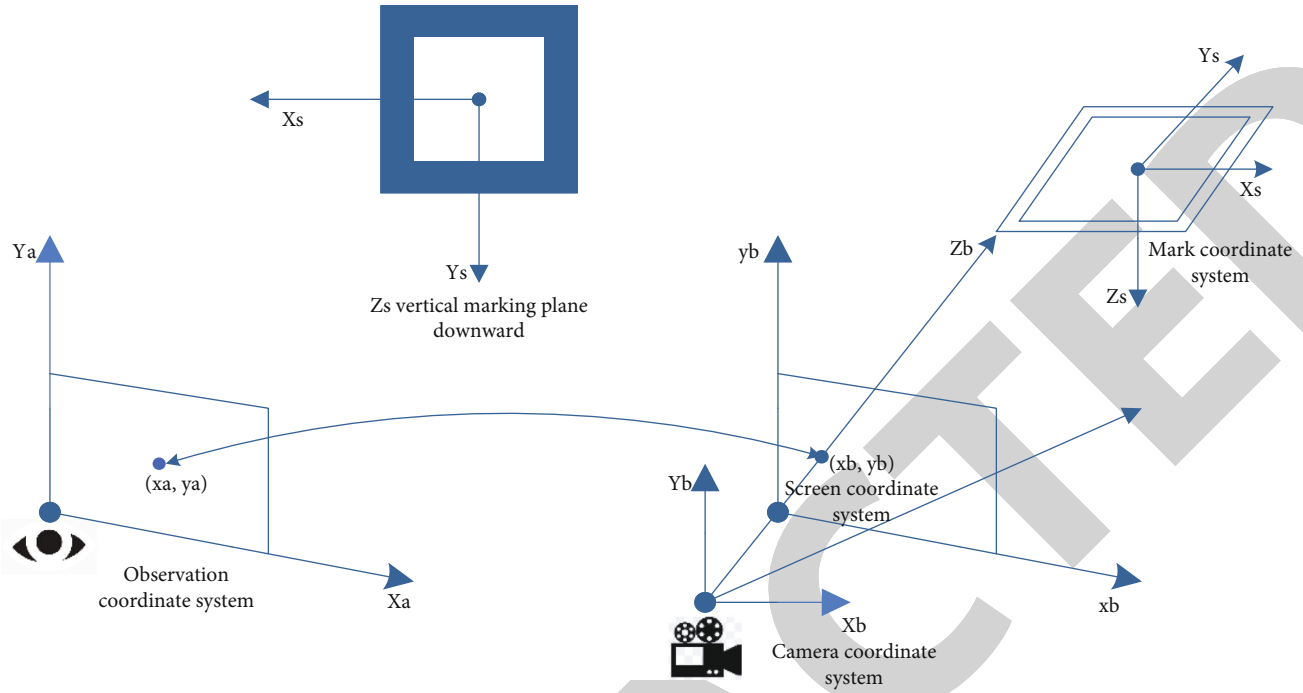


FIGURE 2: ARToolKit coordinate system.

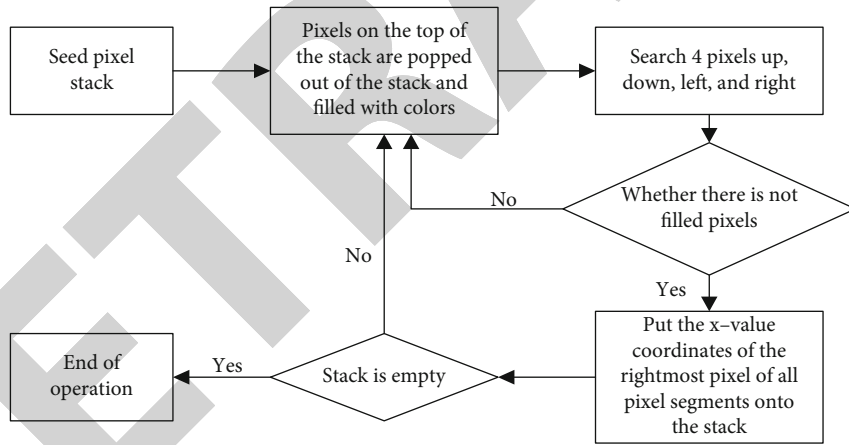


FIGURE 3: Classic target tracking algorithm.

2.3. *Animation Fusion Technology.* The ARToolKit animation fusion process of AR is to start the ARToolKit module, the camera collects the video image of the actual scene, and the system renders and synthesizes the augmented reality video image. For AR products, the quality requirements for animated images are definitely getting higher and higher, and to ensure the quality of 3D animated pictures and videos, the animation must be fused. This article applies animation fusion technology to the fusion processing of 3D animation images. The color distribution technology is used to extract the color components of the 3D animation image, optimize the pixel characteristics, calculate the correlation coefficient of the matching window, and realize the dynamic information

fusion processing of the 3D animation image. In color matching technology, H = hue, which determines what color it is, S = purity, which determines the shade of the color, and B = lightness, which determines how bright the white light shining on the color is. Using the difference discrimination method, that is, fast and slow, bright and dark, heavy and light, etc., the opposite adjectives are evaluated using a 5-stage or 7-stage scale. Simulation results show that this method can improve the peak signal-to-noise ratio of image output and improve the quality of dynamic images. Since camera capture is particularly important in the process of animation fusion, how to accurately locate the camera is also the focus of our attention [19, 20].

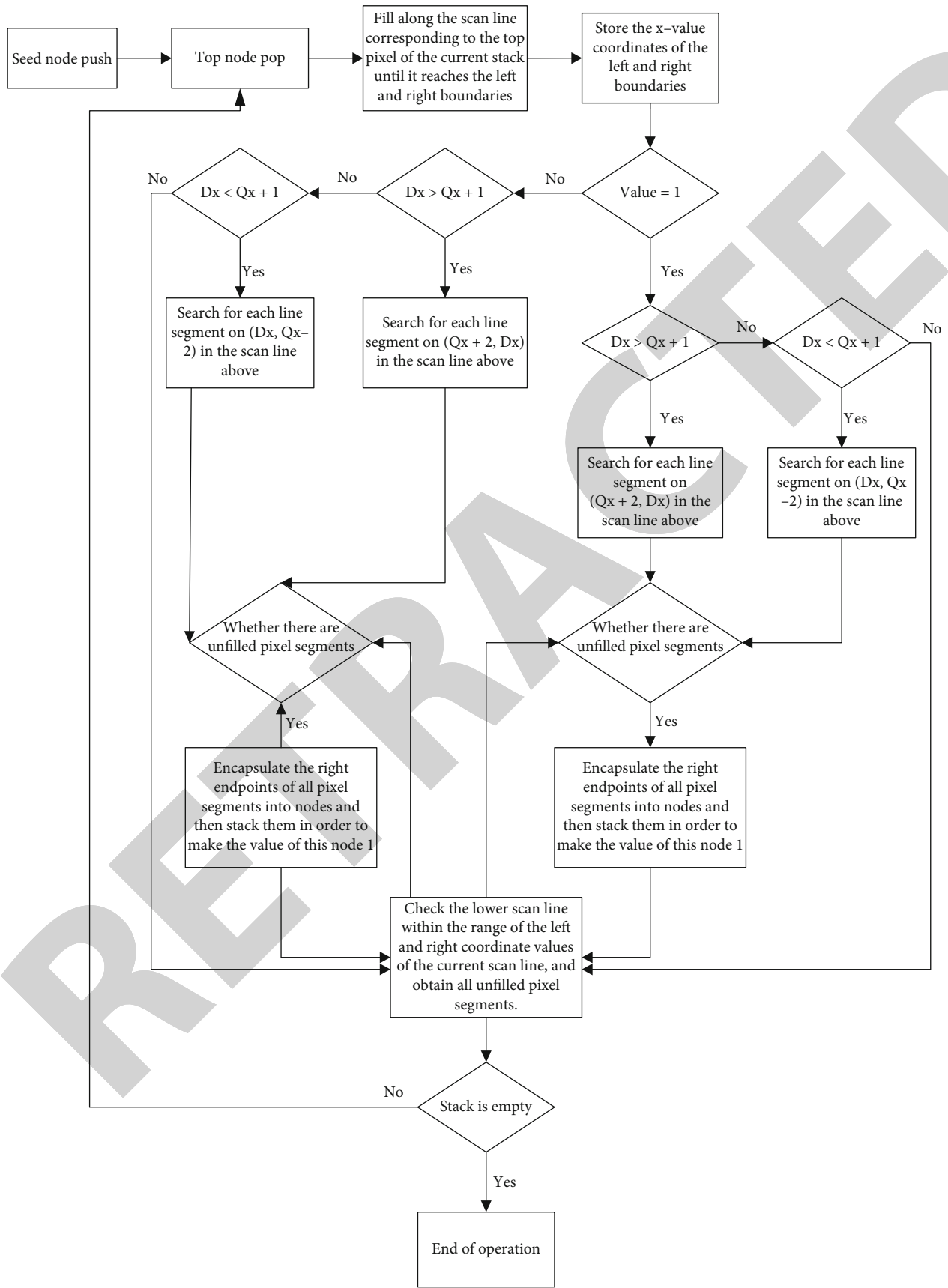


FIGURE 4: Improved target tracking algorithm.



**2.3.1. Camera Position and Attitude.** For the camera pose, a feature-based image registration algorithm can be used to eliminate the difference, so the calculation of the camera pose parameter is stable to the difference. The information parameters are calculated through the correspondence between 2D and 3D using the LM algorithm, thereby minimizing the average projection error [21], as shown in

$$\min_{P_c} \sum_j \|w_{c_j}(Y_{c_j} - \bar{Y}_{c_j})\|^2. \quad (13)$$

Among them,  $c$  is the index of the current image tilt, and  $P$  is the parameter information of the camera pose.

**2.3.2. Camera Antishake.** The above algorithm will shake the virtual objects under certain conditions. In order to eliminate this phenomenon, parameter  $K$  is introduced for calculation. The improved camera parameters are shown in the following formula:

$$\min_{P_c} \sum_j \|w_{c_j}(Y_{c_j} - \bar{Y}_{c_j})\|^2 + K, \quad (14)$$

$$K = \lambda^2 \|W(p_c - p_{c-1})\|^2. \quad (15)$$

Among them,  $W$  is the diagonal matrix  $6 \times 6$ ,  $\lambda$  is the stationary coefficient, and  $P_{c-1}$  is the parameter estimated in the previous frame.

Considering the smoothness of the stationary coefficient  $\lambda$  in the camera motion, virtual image delay will occur, so parameter  $K$  needs to be within a certain range. This range is represented by  $S$ , namely,

$$\begin{aligned} \lambda^2 \|W(p_c - p_{c-1})\|^2 &\leq S, \\ S &= \gamma^2 M. \end{aligned} \quad (16)$$

Among them,  $\gamma$  is the indefinite coefficient of image measurement, and  $M$  is the image pixel.

From this, we can get the calculation formula of  $\lambda$ :

$$\lambda^2 = \frac{\gamma^2 M}{\|W(p_c - p_{c-1})\|^2}. \quad (17)$$

The calculation method first uses formula (13) to calculate  $P_c$ ; at this time,  $\lambda$  is 0, uses iterative calculation, and then uses formula (14) to get the camera parameters [22].

**2.3.3. Special Circumstances.** If the coordinates are unknown and the lens is defective, the image taken by the camera will be distorted. If the lens is defective, replace it directly. If the coordinates are not known, it can use the three points in the known image and their mapping points to obtain the parameter values and use the principle of linear distortion. Then, use formulas (18) and (19) to calculate the coordinates  $(x_0, y_0)$  [23].

$$x_0 = a_1 x' + b_1 y' + c_1, \quad (18)$$

$$y_0 = a_2 x' + b_2 y' + c_2. \quad (19)$$

### 3. ARToolKit Target Tracking and Animation Fusion Experiment

#### 3.1. Experimental Design

**3.1.1. AR Simulation Test Experiment Based on Edge Computing.** In order to get the actual value conveniently, this paper simulates the data for experimental testing. Assuming that there are 11 users in an area using the AR application and the transmission signal in this area is stable and meets the transmission conditions of formula (3), the simulation data is shown in Table 1. Using the equal power allocation principle, the relationship between the maximum uplink transmission power and the maximum downlink power and the minimum delay time can be obtained, as shown in Figure 5.

It can be seen from Figure 5 that in order to make the minimum delay time approximately 0.1 s, the uplink transmission power should not be lower than 1.2W. If the delay time is above 0.1 s, the required power can be significantly reduced. When the required delay time is less than 0.1 s, due to the limited transmission rate, a large increase in power cannot significantly reduce the delay. In addition to the internal factors of the cloud computing system in the downlink, the transmission rate is affected by the strength of the link transmission signal, and the signal strength decreases with distance, as shown in formula (4). With the increase of power, the delay time is shortened within a certain range, but also due to the limited transmission rate, a large increase in power cannot significantly reduce the delay [24].

**3.1.2. Edge Computing and Cloud Computing Testing.** After the user starts the AR program, the data is continuously transmitted to the receiver during use, and after the data is received, the data is calculated at the edge of the cloud. In order to compare the difference between edge computing and cloud computing, we divide users into two groups under different powers in an ideal state and use edge computing and traditional cloud computing to compare the delay time of the two processing. Using formula, the real-time parameter information of the camera can be calculated to obtain Table 2. Finally, the cloud computing data and the processing delay data of edge computing are compared in a chart, as shown in Figure 6.

It can be seen from Figure 6 that under the same computing power, the processing delay time of the AR program using edge computing is significantly lower than that of cloud computing. And within a certain power range, when the power increases, the time for both types will decrease, but the rate of decrease will slow down and even become stable. In addition, after data comparison, the processing delay of edge computing is only about 1/3 of cloud computing. Feedback after user experience also shows that AR programs

TABLE 1: Simulation parameter setting.

Parameter	Simulation value
Number of users	11
Noise power spectral density $\delta_0$	$10^{-10}$
Total uplink and downlink transmission bandwidth $B^u, B^d$	$10^8$ Hz
Maximum transmission power of uplink users $P_{\max}^u$	0.5 W
Maximum transmission power of downlink transmitter $P_{\max}^d$	25 W
Computing speed	$10^{12}$ CPU/s
Downlink user receiving data energy $e_n^d$	0.825 J/s
The amount of data each user needs to transmit $B_n^u$	$10^7$ bit
The amount of data each user needs to receive $B_n^d$	$10^7$ bit

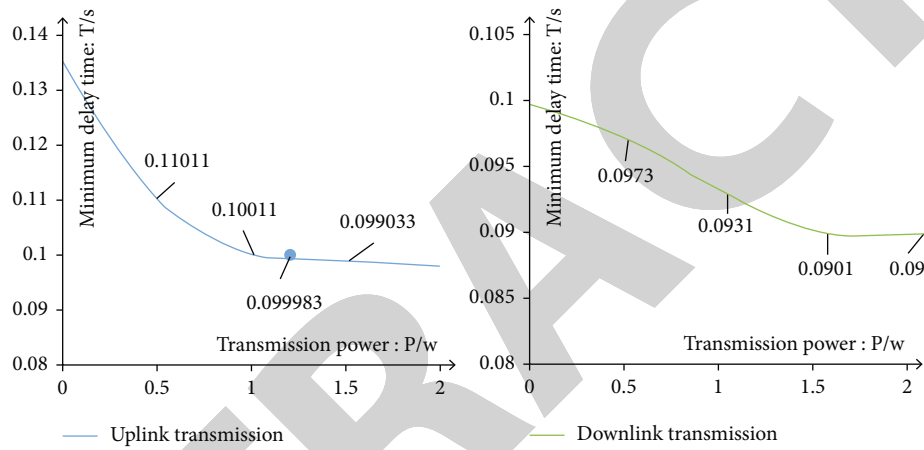


FIGURE 5: The relationship between uplink and downlink power and minimum delay time.

TABLE 2: Delay time of computing.

Computing power	Delay time of cloud computing	Delay time of edge computing
10 W	3.132 s	1.062 s
20 W	2.573 s	0.863 s
30 W	2.432 s	0.816 s
40 W	2.331 s	0.776 s

using edge computing are significantly smoother and much clearer [25].

**3.1.3. AR Industry Market Survey.** At present, the AR industry is an emerging technology that is more popular with users. In order to understand the current situation of the AR market and the future development prospects of the AR industry, this article conducts a random survey of citizens in several cities through questionnaires. 2000 citizens were surveyed from City A to analyze the public's views on AR technology in terms of whether they knew or used AR and the use of AR products, to understand the market situation of AR and the public's familiarity. According to the survey data, it is drawn as shown in Figure 7.

As shown in Figure 7, the survey includes citizens' knowledge of the AR industry, including those who know and use AR products, those who know but have not used them, and those who have not known and have not used them. And citizens who have used AR products analyzed their uses in three major categories, namely, education, entertainment, and other categories. Of the 3000 citizens surveyed, 1627 have knowledge and use of the AR industry, accounting for more than half, indicating that AR products are very popular. In addition, there are 2613 people who know AR, accounting for 87.1% of the total, indicating that AR technology and products have been widely recognized by the public. Among the 1627 people who use AR products, 832 are used for entertainment, which is more than half of the total number of users. This also shows that AR technology products are mostly used in the entertainment industry and are more popular. In addition, there are 123 people who used it for education, which also shows that AR products have played a certain role in the education industry. However, there are not a small number of people who know it but have not used it. There are 986 people out of 3000 citizens, which is close to one-third of the total number.

According to a comprehensive survey, 87.1% of citizens know about AR. At present, the promotion of AR products

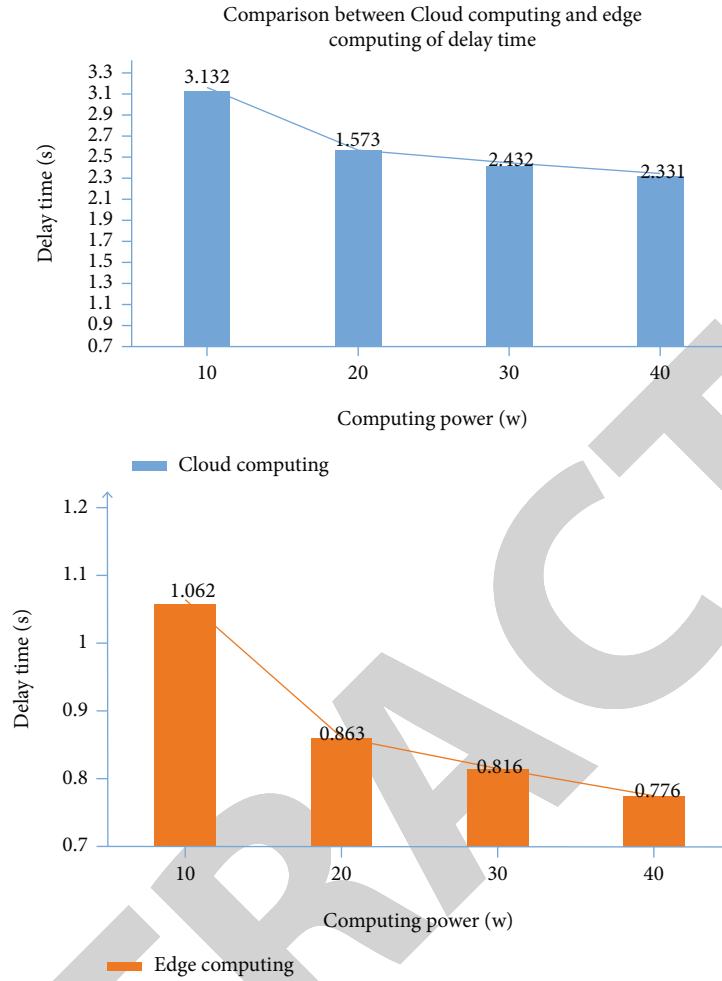


FIGURE 6: Comparison of latency between edge computing and cloud computing.

is still very widespread, and people are still very interested in AR technology. However, from the information that one-third of the people know but have not used, it can be seen that the current AR products on the market are not enough to attract the public, or the current AR product quality needs to be improved. Therefore, the current development of high-quality AR products is a market need as well as a mass demand [26].

**3.1.4. ARToolKit's Target Tracking Technology Test.** Countermeasures and pilot projects to improve the target efficiency, use the same source of actual use of equipment, and calculate the scanner drawing time. In Table 3, it can be seen that the improved algorithm can reduce the number of element stacks and reduce the number of elements. And being time-consuming is about one-third of the classic algorithm.

In order to compare the differences between the two more intuitively, this paper makes the efficiency graphs of the two algorithms. It can be seen from Figure 8 that after a horizontal comparison, the minimum calculation time of the improved tracking algorithm is less than 0.5 s, while the classic algorithm is more than 0.5 s, which is shorter than

the classic algorithm. At the same calculation time, the improved algorithm can process more stack elements. After longitudinal comparison, for the same number of stack elements, the calculation time of the improved algorithm is significantly lower than that of the classic algorithm, and the number of element stacks of the improved tracking algorithm is less than that of the classic algorithm, and the minimum and maximum element stack numbers are also significantly reduced [27].

**3.1.5. Animation Fusion Test.** After using target tracking technology to capture video or pictures, the next final step of animation fusion is also particularly important. The aforementioned 3D animation image dynamic information fusion technology based on two-dimensional color space matching as well as the precise positioning and antishake theory of the camera requires experiments to prove its accuracy, and experiments are carried out for the pictures, videos, and data collected in the previous section.

Simulation experiments verify the performance of this method in realizing dynamic information fusion of 3D animation images. The experiment uses the standard image of the test data set of 3D animation images, 1800 image sample

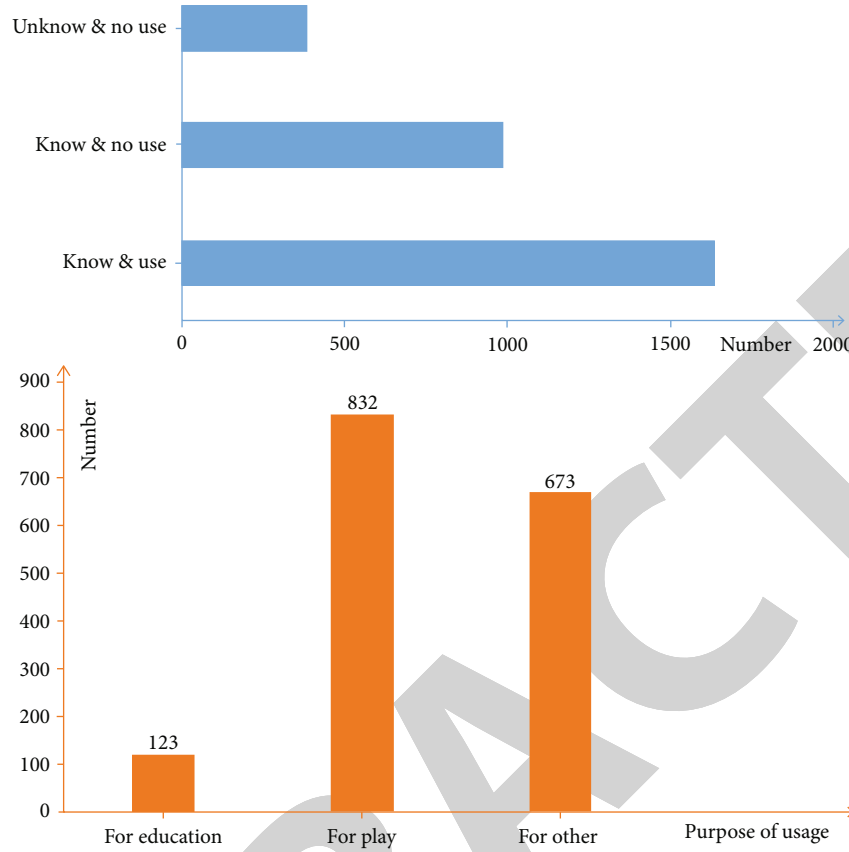


FIGURE 7: Survey on the situation of citizens on the AR industry.

TABLE 3: Algorithm efficiency comparison.

Mimic marker	Coordinate	Number of stacks of classical algorithm elements	Number of stacks of improved algorithm elements	Classic algorithm time (ms)	Improved algorithm time (ms)
A	(3, 11)	135652	8654	1996.562	669.338
B	(-6, 14)	85643	5021	1135.231	341.223
C	(13,-8)	684326	12360	3013.321	1007.136
D	(7, 12)	464566	10125	2979.645	956.253
E	(-8,-13)	66552	4665	1033.232	302.427

sets, the edge contour pixel distribution of the 3D animation image is  $100 \times 230$ , and the image color texture matching coefficients are 0.12 and 0.18, respectively. According to the above parameter settings, the three-dimensional animation image test sample object is shown in Figure 9. The comparison can clearly see the difference after fusion [28]. The picture comes from Baidu Image Search.

In order to use data to illustrate, this article uses various methods to test the output signal-to-noise ratio of the image dynamic information fusion. According to the previous formula and the number of calculations, the ratio values of the two are obtained. The higher the peak signal-to-noise ratio, the better the quality of the output image. In order to reduce the experimental error, using the data to visually see the dif-

ference between the two fusion calculations, two sets of the same experiment were carried out. The first set of experimental data is before the comma, and the second set of experimental data is after the comma. The comparison result is shown in Figure 10.

It can be seen from Table 4 and Figure 10 that as the number of calculations increases, the output peak signal-to-noise ratio also increases. And compared with the gray value algorithm, the algorithm in this paper only needs half the number of calculations to achieve the same image quality. This shows that the color distribution animation fusion technology can be used for dynamic information processing of 3D animation images and can improve the peak signal-to-noise ratio of image output, that is, improve the quality of animation images [29].

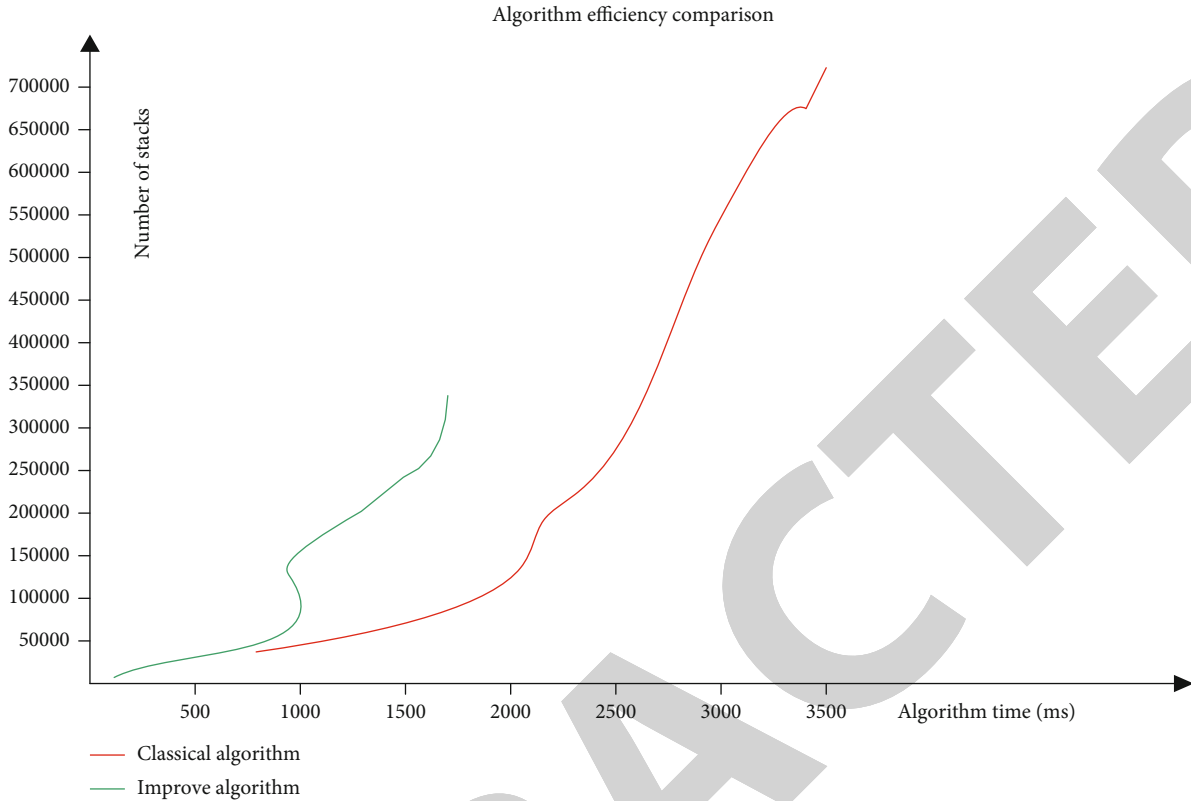


FIGURE 8: Comparison of classic AR algorithm and improved AR target tracking algorithm.



FIGURE 9: Convergence test comparison.

#### 4. Discussions

In the experiment of edge computing and traditional cloud computing, through the functional relationship of the model, the graph data is compared, and it is concluded that the processing speed of the AR program using edge computing is significantly faster, and the virtual pictures and videos are smoother and clearer. And the processing delay of edge computing is only about 1/3 of cloud computing.

In the research experiment of ARToolKit target tracking technology, we improved the classic target tracking algorithm. Although the improved algorithm flow is a bit more complicated, compared with the classic algorithm, the stack space is significantly reduced, the program operation efficiency is improved, and the redundant calculations that are repeated multiple times are avoided.

In the investigation and research on the social status of augmented reality AR, we know that products created by

AR technology have formed a broad market, and the public has high expectations for high-quality AR products. With the improvement of people's living conditions, this expectation will become higher and higher. Therefore, research and development of high-quality AR products is a social need and a need of the masses. In the simulation experiment of animation fusion technology, the principle of color distribution is used to compare and analyze the data of the tested animation. Compared with the traditional fusion technology, the peak output signal-to-noise ratio is higher, the pictures processed by the animation fusion of the color distribution model are obviously more vivid and clear, and the video picture quality is higher [30].

#### 5. Conclusions

This paper analyzes the current development of edge computing, constructs a mathematical model to compare



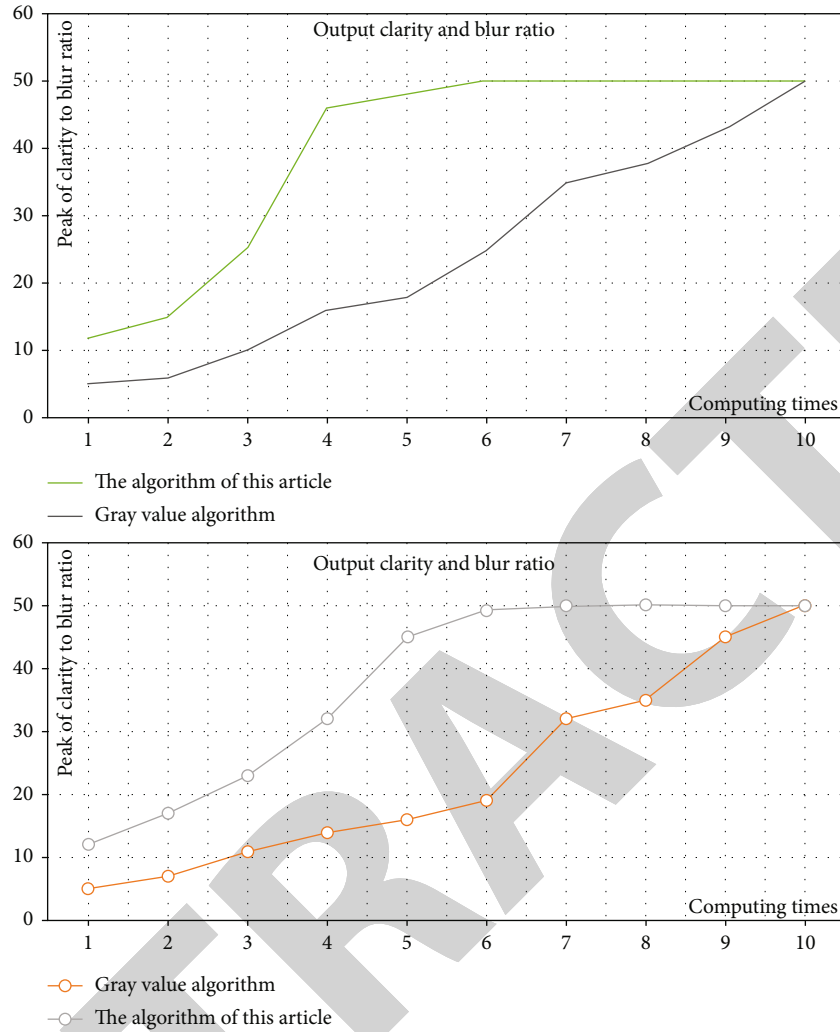


FIGURE 10: Output signal-to-noise ratio.

TABLE 4: Peak of clarity and blur ratio of algorithm.

Computing times	Ratio of gray value algorithm	Ratio of this algorithm
1	5, 5	12, 12
2	6, 7	15, 14
3	10, 11	25, 23
4	16, 14	46, 44
5	18, 16	48, 47
6	25, 24	50, 49
7	35, 32	50, 50
8	38, 37	50, 50
9	43, 45	50, 50
10	50, 50	50, 50

the difference between edge computing and traditional cloud computing, studies the target tracking calculation of ARToolKit, proposes a more efficient and improved algorithm, studies a high-quality animation fusion technology

algorithm, analyzed and investigated the current social status and future prospects of the AR industry, and carried on the experiment analysis and the data chart analysis to the research content. Finally, it is concluded that the target tracking and fusion technology based on edge computing and augmented reality can greatly shorten the calculation time of target tracking and animation fusion and improve work efficiency. The calculation delay time is only 1/3 of the traditional cloud computing, and the work efficiency is increased by about 2 times. And compared with traditional cloud computing, the AR scene animation obtained is clearer under the same number of calculations, and the time to reach the high peak of the signal-to-noise ratio is only about 1/2 of that of traditional cloud computing.

**Data Availability**

No data were used to support this study.

**Conflicts of Interest**

There is no potential conflict of interest in this study.

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## References

- [1] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, “Edge computing: vision and challenges,” *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 637–646, 2016.
- [2] M. Satyanarayanan, “The emergence of edge computing,” *Computer*, vol. 50, no. 1, pp. 30–39, 2017.
- [3] T. Taleb, K. Samdanis, B. Mada, H. Flinck, S. Dutta, and D. Sabella, “On multi-access edge computing: a survey of the emerging 5G network edge cloud architecture and orchestration,” *IEEE Communications Surveys & Tutorials*, vol. 19, no. 3, pp. 1657–1681, 2017.
- [4] Y. Mao, J. Zhang, S. H. Song, and K. B. Letaief, “Stochastic joint radio and computational resource management for multi-user mobile-edge computing systems,” *IEEE Transactions on Wireless Communications*, vol. 16, no. 9, pp. 5994–6009, 2017.
- [5] K. Zhang, Y. Mao, S. Leng, Y. He, and Y. Zhang, “Mobile-edge computing for vehicular networks: a promising network paradigm with predictive off-loading,” *IEEE Vehicular Technology Magazine*, vol. 12, no. 2, pp. 36–44, 2017.
- [6] L. He, K. Ota, and M. Dong, “Learning IoT in edge: deep learning for the Internet of things with edge computing,” *IEEE Network*, vol. 32, no. 1, pp. 96–101, 2018.
- [7] S. Blanco-Pons, B. Carrion-Ruiz, J. Luis, and J. L. Lerma, “Augmented reality application assessment for disseminating rock art,” *Multimedia Tools and Applications*, vol. 78, no. 8, pp. 10265–10286, 2019.
- [8] W. Shi and S. Dustdar, “The promise of edge computing,” *Computer*, vol. 49, no. 5, pp. 78–81, 2016.
- [9] D. Sabella, A. Vaillant, P. Kuure, U. Rauschenbach, and F. Giust, “Mobile-edge computing architecture: the role of MEC in the Internet of things,” *IEEE Consumer Electronics Magazine*, vol. 5, no. 4, pp. 84–91, 2016.
- [10] M. Akçayır, G. Akçayır, H. M. Pektaş, and M. A. Ocak, “Augmented reality in science laboratories: the effects of augmented reality on university students’ laboratory skills and attitudes toward science laboratories,” *Computers in Human Behavior*, vol. 57, pp. 334–342, 2016.
- [11] E. Marchand, H. Uchiyama, and F. Spindler, “Pose estimation for augmented reality: a hands-on survey,” *IEEE Transactions on Visualization & Computer Graphics*, vol. 22, no. 12, pp. 2633–2651, 2016.
- [12] M. T. Dieck, T. Jung, and D. I. Han, “Mapping requirements for the wearable smart glasses augmented reality museum application,” *Journal of Hospitality & Tourism Technology*, vol. 7, no. 3, pp. 230–253, 2016.
- [13] A. Javornik, “Augmented reality: research agenda for studying the impact of its media characteristics on consumer behaviour,” *Journal of Retailing and Consumer Services*, vol. 30, no. 4, pp. 252–261, 2016.
- [14] T. C. Huang, C. C. Chen, and Y. W. Chou, “Animating eco-education: to see, feel, and discover in an augmented reality-based experiential learning environment,” *Computers & Education*, vol. 96, pp. 72–82, 2016.
- [15] J. Scholz and A. N. Smith, “Augmented reality: designing immersive experiences that maximize consumer engagement,” *Business Horizons*, vol. 59, no. 2, pp. 149–161, 2016.
- [16] E. Z. Barsom, M. Graafland, and M. P. Schijven, “Systematic review on the effectiveness of augmented reality applications in medical training,” *Surgical Endoscopy*, vol. 30, no. 10, pp. 4174–4183, 2016.
- [17] M. D. De Assuncao, A. D. S. Veith, and R. Buyya, “Distributed data stream processing and edge computing: a survey on resource elasticity and future directions,” *Journal of Network & Computer Applications*, vol. 103, pp. 1–17, 2018.
- [18] T. Jiang, M. Zhu, T. Zan, B. Gu, and Q. Li, “A novel augmented reality-based navigation system in perforator flap transplantation — a feasibility study,” *Annals of Plastic Surgery*, vol. 79, no. 2, pp. 192–196, 2017.
- [19] C. Pang, S. C. Huang, J. C. Liu, and W. Zhao, “Multi sensor cross cueing technology and its application in target tracking,” *Yuhang Xuebao/Journal of Astronautics*, vol. 38, no. 4, pp. 401–409, 2017.
- [20] X. Wang, X. Sheng, H. Yu, L. Guo, and J. Yin, “Target tracking technology for reducing false alarm,” *Acoustical Society of America Journal*, vol. 141, no. 5, pp. 3918–3918, 2017.
- [21] S. Fujita, Y. Sato, T. Kuwahara, Y. Sakamoto, and K. Yoshida, “Development and ground evaluation of ground-target tracking control of microsatellite RISESAT,” *Transactions of the Japan Society for Aeronautical and Space Sciences, Aerospace Technology Japan*, vol. 17, no. 2, pp. 120–126, 2019.
- [22] T. Long, Z. Liang, and Q. Liu, “Advanced technology of high-resolution radar: target detection, tracking, imaging, and recognition,” *Science China Information Sciences*, vol. 62, no. 4, pp. 1–26, 2019.
- [23] J. Hou and B. Li, “Swimming target detection and tracking technology in video image processing,” *Microprocessors and Microsystems*, vol. 80, no. 3, pp. 103535–103543, 2021.
- [24] Y. Wang, J. Yue, Y. Dong, and Z. Hu, “Review on kernel based target tracking for autonomous driving,” *Journal of Information Processing*, vol. 24, no. 1, pp. 49–63, 2016.
- [25] Y.-L. Hsu, P.-H. Chou, H.-C. Chang et al., “Design and implementation of a smart home system using multisensor data fusion technology,” *Sensors*, vol. 17, no. 7, pp. 1631–1642, 2017.
- [26] X. Yang, W. A. Zhang, L. Yu, and K. Xing, “Multi-rate distributed fusion estimation for sensor network-based target tracking,” *IEEE Sensors Journal*, vol. 16, no. 5, pp. 1233–1242, 2016.
- [27] A. T. Kamal, J. H. Bappy, J. A. Farrell, and A. K. Roy-Chowdhury, “Distributed multi-target tracking and data association in vision networks,” *IEEE Transactions on Pattern Analysis & Machine Intelligence*, vol. 38, no. 7, pp. 1397–1410, 2016.

- [28] A. Amamra and N. Aouf, "Real-time multiview data fusion for object tracking with RGBD sensors," *Robotica*, vol. 34, no. 8, pp. 1855–1879, 2016.
- [29] S. J. Ahn, S. U. Han, and M. Al-Hussein, "2D drawing visualization framework for applying projection-based augmented reality in a panelized construction manufacturing facility: proof of concept," *Journal of Computing in Civil Engineering*, vol. 33, no. 5, 2019.
- [30] T. Liao, "Is it 'augmented reality'? Contesting boundary work over the definitions and organizing visions for an emerging technology across field-configuring events," *Information and Organization*, vol. 26, no. 3, pp. 45–62, 2016.

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