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Research Article

Perceived Integrity of Distributed Streaming Media Based on AWTC-TT Algorithm Optimization

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With the development of economy, more and more attention has been paid to the monitoring system, which provides a reliable and powerful guarantee for people's daily life, property security, and national security. The intelligent video surveillance introduces computer vision-related technologies into traditional video surveillance and realizes the analysis and understanding of video data without artificial dependence to obtain valuable target information in the perceived video data. On this basis, functions such as abnormal event monitoring and real-time alarm are realized. Distributed streaming media monitoring has changed the manual-based monitoring and content analysis modes of traditional monitoring, but the high-complexity calculations such as motion estimation and motion compensation in the encoding process increase the burden of monitoring and sensing equipment. Especially with the development of wireless multimedia technology, the traditional video coding has been unable to meet the requirements of monitoring and sensing equipment in the monitoring system based on wireless technology. This paper proposes an adaptive weighted tensor completion algorithm to complete the repair of streaming media data perceived by ordinary sensing devices. In the proposed algorithm, considering the unbalanced information distribution and data redundancy problems that may exist in the data, the tensor data is adjusted according to the approximate solution algorithm to obtain tensor data that only retains important information and the information distribution is more balanced and reasonable. In the iterative solution process, in order to better map the impact of each dimension of data in the repair process, an adaptive weighting mechanism is proposed according to the data characteristics to obtain the corresponding weight value of each dimension of data. Finally, the proposed approximate tensor solving algorithm and adaptive weighting mechanism are applied to a simple low-rank tensor completeness algorithm based on tensor columns to form the algorithm of this paper, and it is used to repair perceptual streaming media data with data missing problems. The experimental results show that the algorithm in this paper can improve the perceived streaming media data quality by 3% based on the known data information and maintain an advantage of 2% in average processing time. It avoids the replacement of sensing equipment and also provides data quality assurance for subsequent sensing streaming media content analysis. It has certain research significance for the development of monitoring system with artificial intelligence management for target perception and tracking.

1. Introduction

The monitoring system uses the sensing equipment to obtain the sensing data and then realizes the extraction of the valuable target information in the sensing streaming media based on the analysis module, laying a data information foundation for abnormal event monitoring, real-time alarms, etc. In order to solve the problem of using ordinary sensing equipment to obtain valuable target information, firstly, the perceptual optimization scheme is studied on the basis of distributed streaming media coding, while meeting the low power consumption and high efficiency requirements of the monitoring system using wireless multimedia technology for the monitoring and sensing equipment Realize the improvement of decoding and perceiving streaming media quality. In the perceptual streaming media acquisition module, due to the limitations of ordinary perceptual devices, it cannot well cope with the influence of interference factors such as light and weather, which inevitably occurs data degradation, resulting in a decrease in the quality of perceptual streaming media data. Research on perception optimization schemes based on streaming media repair algorithms, and realize the optimization of perception streaming media while avoiding the replacement of expensive perception equipment. Among them, consider the monitoring scene using wireless multimedia technology, and carry out the research on the streaming media repair algorithm on the monitoring side [1].

The earliest solutions used in data restoration include matrix-based correlation algorithms. However, in practical problems, data is often affected by many factors and thus has a higher dimension. The expression of the matrix can no longer fully describe the multiple linear relationships in the data. Therefore, tensor enters people's field of vision. Based on the successful application of low-rank matrices in repair algorithms, scholars have applied the concept of low-rank to tensors and carried out related research under the concept of low-rank tensors. According to different methods, low-rank tensor related research can be divided into low-rank tensor completeness problem, low-rank tensor approximation problem, and low-rank tensor robust principal component analysis problem [2]. In streaming media repair, the data missing problem in the data degradation phenomenon can be marked as a missing value estimation problem, and the perceived streaming media data with the data missing problem can be repaired by establishing the relationship between the known data elements and the unknown elements. The unbalanced information distribution, redundant information, and underutilization of tensor data information in the perception data may affect the performance of the streaming media repair algorithm. In response to this problem, this paper conducts research based on the low-rank tensor completeness problem to complete the repair of perceptual streaming media with data missing problems, avoiding the replacement of expensive perceptual equipment and providing data quality assurance for subsequent perceptual streaming media content analysis [3].

In recent years, research on data restoration based on the completeness of low-rank tensors has achieved certain results. For example, Qiu et al. [4] first successfully extended the matrix to the case of tensors. Three algorithms for solving convex optimization problems are proposed: Simple Low-Rank Tensor Completion (SiLRTC), Fast Low-Rank Tensor Completion (FaLRTC), and High Accuracy Low-Rank Tensor Completion (HaLRTC). Hu et al. [5] proposed a method of automatically adjusting parameters, using CP decomposition and full Bayesian processing formulated by a hierarchical probability model, by appropriately setting the parameters between multiple latent factors and superfactors on all hyperparameters. A spaRSE prior is introduced to complete the automatic determination of the rank. Hima et al. [6] proposed a new low-rank tensor model based on cyclic algebra, that is, the twist Tensor Nuclear Norm (t-TNN) algorithm. Chen and Zhou [7] focused on the method of repairing missing areas in streaming media after removing unwanted moving objects. Nie et al. [8] proposed a novel Sequential Tensor Completion algorithm (STC) to repair network traffic data. On the basis of Tucker decomposition, Tokmakov et al. proposed the concept of tensor column; on this basis, literature [9] introduced the concept of tensor column into the SiLRTC algorithm and Tensor Completion by Parallel Matrix Factorization (TMac), the Simple Low-Rank Tensor Completion via Tensor Train (SiLRTC-TT), and Parallel Matrix Factorization for low-rank Tensor Completion via Tensor Train, (TMAC-TT), and then combined with the advantages of tensor columns to better obtain global information to complete the restoration of data such as color image streaming. Li et al. [10] proposed spaRSE Tensor-train Optimization (STTO) based on the concept of tensor columns. The algorithm treats incomplete data as spaRSE tensors and then finds them based on the first-order optimization algorithm.

For the perceptual streaming media acquisition module, the streaming media repair algorithm can alleviate the problem of data quality degradation caused by the limitations of ordinary perceptual devices; and in the perceptual analysis module, the streaming media target segmentation algorithm can extract massive perceptual streaming media target information. But there are still some problems:

(1) First, the quality of decoded streaming media in a distributed streaming media coding scheme depends on the quality of side information to a certain extent, and perceiving interference factors such as complex environments in streaming media will affect the generation of side information and reduce the quality of decoded streaming media

(2) Moreover, in the perceptual streaming media repair task with the problem of data loss, the unbalanced information distribution in the data, redundant information, and insufficient use of tensor data information will affect the repair performance of the streaming media repair algorithm

(3) Finally, the streaming media target motion and target deformation will affect the quality of streaming media segmentation targets. Therefore, it is necessary to establish an adaptive target segmentation model for mass perception streaming media that can cope with the negative effects of target motion and deformation, in order to realize the reliable extraction of perceptual streaming media target information

Inspired by the existing research on the completeness of low-rank tensors, according to the Tensor Train rank (TT-rank) can take advantage of the global hidden information in the tensor data, this paper proposes a TT-rank-based adaptive weighted tensor completion algorithm to complete the repair of missing data. Taking into account the possible imbalance of data distribution or redundant information in streaming media data, an approximate tensor solving algorithm is first introduced to adjust the tensor data to obtain tensor data that only retains important information and has a more balanced information distribution. Second, according to the data characteristics, an adaptive weighting mechanism is adopted to adjust the weight corresponding to each dimension of the data in the repair process. Theoretical analysis and experiments show that the proposed algorithm presents better repair performance than existing algorithms.

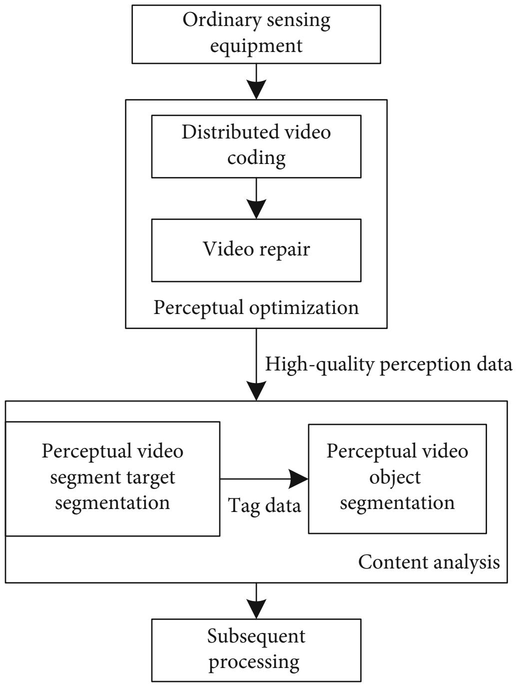


Figure 1: Framework diagram of the scheme proposed in this paper.

In order to meet the requirement of using ordinary sensing equipment to achieve reliable extraction of target information, this paper designs a streaming media processing framework as shown in Figure 1.

First of all, for the problems of the data encoding module and the perceptual streaming media acquisition module in the monitoring system, combined with distributed streaming media encoding and streaming media repair, the perceptual optimization scheme is studied to obtain higher-quality perceptual streaming media data. Second, for the perceptual analysis module, the content analysis scheme is studied on the basis of the streaming media target segmentation algorithm to establish an adaptive target segmentation model for mass perceptual streaming media data and complete the reliable extraction of mass perceptual streaming media target information. In this paper, perceptual streaming media segment is an intercepted segment of perceptual streaming media. First, the perceptual streaming media segment target segmentation algorithm is used to achieve effective segmentation of the perceptual streaming media segment target, and the segmentation result is used as tag data in the perceptual streaming media target segmentation scheme, so that the perceptual streaming media target segmentation scheme can better adapt to perception. Streaming media characteristics, under the interference of factors such as streaming media target movement and target deformation, complete the adaptive segmentation of mass-perceived streaming media targets and realize the reliable extraction of target information of mass-perceived streaming media data.

The main contributions of this paper are as follows:

(1) To meet the low power consumption and high efficiency requirements of the monitoring system, use the wireless multimedia technology for the sensing equipment. Research on distributed streaming media encoding algorithms, and address the problem of degradation of decoded data quality caused by interference factors such as streaming media background environment and target motion in distributed streaming media encoding schemes. Then, a prediction-based side information generation algorithm is proposed to meet the needs of wireless multimedia. The technical monitoring system requires high-quality decoded perceptual streaming media data at the same time

(2) Aiming at the problem of the degradation of the perceived data quality caused by the inability of ordinary sensing equipment to cope with the influence of interference factors, such as light and weather, the problem of data loss in the phenomenon of data degradation is studied. A streaming media completion algorithm based on tensor column rank is proposed to realize the optimization of streaming media data while avoiding the replacement of expensive sensing equipment

The specific content of each chapter of the full text is as follows:

Section 1 introduces the background and significance of the topic selection;

Section 2 introduces the theoretical basis and research status of the research involved.

Section 3 designs the streaming media completion algorithm of tensor column rank.

Section 4 realizes the optimization of perceived streaming media data quality while avoiding the replacement of expensive sensing equipment.

Section 5 performs performance verification and analysis through simulation experiments.

Section 6 summarizes this paper and introduces the outlook for the next stage of work.

2. Related Work

In order to meet the demand of obtaining valuable and reliable target information through ordinary sensing equipment, firstly, in view of the problems of the data encoding module in the monitoring system, a perceptual optimization scheme is studied based on distributed streaming media encoding. The theoretical basis and current research results of distributed streaming media coding are introduced.

2.1. Distributed Streaming Media Coding Algorithm. Different from the joint coding and decoding method of traditional streaming media coding, the distributed streaming media coding adopts independent coding and joint decoding. The theoretical basis of distributed streaming media coding is Slepian-Wolf (SW) and Wyner-Ziv (WZ) two theorems [11]. SW is also called lossless distributed source coding. The SW theorem shows that independent coding and joint decoding of related sources (obtaining side information Y at the decoding end)

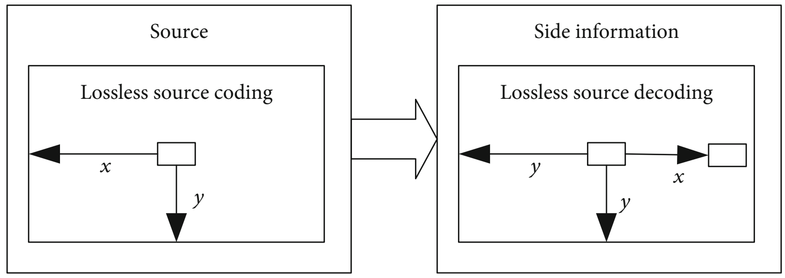


Figure 2: Lossless compression of X using statistical side information Y.

can still be the same as joint coding and joint decoding (obtaining side information Y at the coding end).

The coding efficiency is shown in Figure 2.

Based on the SW theory, Song et al. extended distributed streaming media coding to the field of lossy coding and proposed a lossy coding theorem based on side information. In this theorem, it is assumed that X and Y are two independent and identically distributed random sequences, where X is the coding sequence and Y is the known side information. Assuming that the reconstructed value of X after decoding is X, the distortion rate $D = E\sqrt{[d(x, \bar{x})]}$ [12]. In the WZ theory, $R_{X|Y}^{WZ}$ (D)represents the rate-distortion function, which represents the lower bound of the bit rate that can be achieved by distributed streaming media encoding when the distortion rate D is given. $R_{X|Y}(D)$ represents the rate-distortion function of the codec using side information Y [13]. WZ proves that when only side information Y is given at the decoding end, $R_{X|Y}^{WZ}(D) \geq R_{X|Y}(D)$. At the same time, it is proved that under the condition of Gaussian memoryless source and mean square error distortion, $R_{X|Y}^{WZ}(D) = R_{X|Y}(D)$. The emergence of SW and WZ theorems laid a theoretical foundation for distributed streaming media coding [14].

2.2. Streaming Media Repair Algorithm. To solve the problem of obtaining reliable target information based on ordinary sensing equipment, in the perceptual streaming media acquisition module, in order to deal with the data quality degradation caused by the influence of factors such as light, weather, and other factors due to the limitations of ordinary perceptual devices, the streaming media repair algorithm is studied to complete the perceptual data optimization and to avoid the replacement of expensive perception. The device also realizes the improvement of the perceived streaming media data quality [15].

A scalar can be regarded as a zero-dimensional tensor and represented by $(x, y, z, \cdots)$; a vector can be regarded as a one-dimensional tensor with bold lowercase letters $(x, y, z, \cdots)$ representation; a matrix can be defined as a two-dimensional tensor with bold capital letters $(X, Y, Z, \cdots)$ to indicate; a tensor has a higher dimension (≥ 3), expressed as $(\alpha, \beta, \varepsilon)$, as $\alpha \in R^{p1, p2, \cdots, p^n}$, and among them, $p = 1, 2, \cdots, n$ is the k-th dimension [16]. Similar to the representation method of the elements in the vector matrix, the elements in the tensor can be expressed as $x_{i_1, i_2, \cdots, i_k}$ and $k = 1, 2, \cdots, n$, and among them, $i_1, i_2, \cdots, i_k$ is the component index of the tensor element. The third-order tensor is shown in Figure 3.

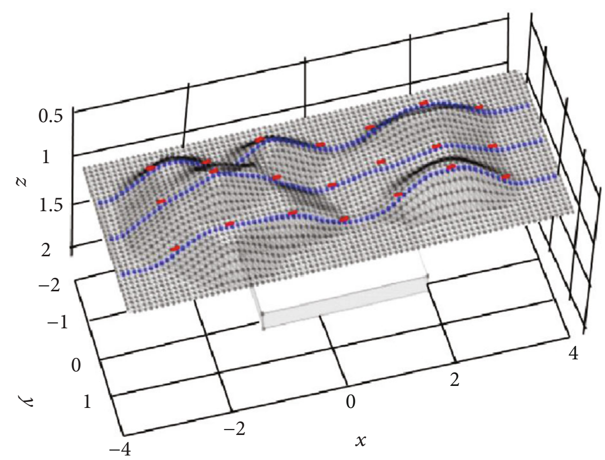


Figure 3: Schematic diagram of the third-order tensor.

In the tensor α, if the $n-1$ component indicators in α are fixed, a vector can be obtained by observing the change of the remaining component indicators, which can be defined as a fiber of the n-th-order tensor. If there are $n-2$ component indexes in α, a matrix can be obtained according to the changes of the remaining 2 component indexes. This process can be called a tensor slicing operation [17].

Through the investigation of the theoretical background of low-rank tensor and related algorithms, in the perceptual streaming media acquisition module, in response to the problem of data quality degradation caused by the limitations of ordinary perceptual devices, the proposed streaming media repair algorithm provides a way to improve the perceptual data quality. It is possible, but in the streaming media repair task with the problem of missing data, the unbalanced information distribution in the perceived data, redundant information, and insufficient use of tensor data information will affect the performance of the repair algorithm [18]. Therefore, it is meaningful to carry out research on perceptual optimization methods based on the completeness of low-rank tensors.

3. Streaming Media Repair Algorithm Based on Tensor Column Rank

Based on the problem of low-rank tensor completeness, this paper uses a repair algorithm for sensing streaming media data in the monitoring system, that is, the adaptive weighted tensor completion algorithm based on TT-rank (AWTC-TT), to solve the problem of ordinary sensing equipment such as weather. The problem of missing perception data caused by interference factors such as light and light.

3.1. Streaming Media Completion Algorithm Based on Tensor Column Rank. It can be used in the field of image streaming media restoration, including matrix-based related methods, such as the problem of low-rank matrix completeness. Based on existing research, the low-rank matrix completeness problem can be defined as the following form:

$$\min_x \text{ rank }(X) \text{ s.t.} X_\Omega = T_\Omega \tag{1}$$

Among them, Ω refers to the set of known elements. The function in formula (1) is an NP-hard problem, and studies have shown that the kernel norm of the matrix is the optimal convex approximation of the matrix rank [19]. Therefore, in the subsequent algorithm, the above form is transformed into the form expressed by formula (2):

$$\min_x \|X\|_* \text{ s.t.} X_\Omega = T_\Omega \tag{2}$$

Among them, $\|X\|_*$refers to the nuclear norm of the matrix. On the basis of the low-rank matrix completeness problem, based on the Tucker rank, the low-rank tensor completeness problem can be defined as follows:

$$\min_{\chi_{(k)}} \sum_{k=1}^{N} \alpha_k \text{ rank }\left(\chi_{(k)}\right) \text{ s.t.} \chi_\Omega = \tau_\Omega \tag{3}$$

Among them, χ, τ is a tensor of order N with the same size, $\alpha_k \geq 0, \sum_{k=1}^{N} \alpha_k = 1$. Since problem (3) is difficult to solve directly, problem (3) is transformed into the following form:

$$\min_{\chi_{(k)}} \sum_{k=1}^{N} \alpha_k \left\|\chi_{(k)}\right\|_* \text{ s.t.} \chi_\Omega = \tau_\Omega \tag{4}$$

In problem (4), $\sum_{k=1}^{N} \alpha_k \|\chi_{(k)}\|_*$ represents the Tucker kernel norm of tensor χ, and $\chi_{(k)} \in \mathbb{R}^{m\times n}(m = I_k \text{ and } n = \prod_{l=1,l\neq k}^{N} I_l)$ is the expansion matrix of the k-th order of the tensorχ. Based on literature [16], the relationship between the elements in $\chi_{(k)}$ depends on the rank r_k, and the rank r_k is related to $m = I_k$ [20]. Therefore, when the dimensionality of each order in the tensor χ is almost the same, that is, $I_1 \approx I_2 \approx I_3 \cdots \approx I_N \approx I$, as $N(N \geq 4)$ or I increases, the phenomenon of $m \ll n$ will appear, resulting in the unbalance problem of the k-th-order expansion matrix $\chi_{(k)}$ of the tensor χ. At the same time, the rank $r_k \in (r_1, r_2, \cdots, r_N)$ may be too small to describe the relationship between tensor elements well [21].

Therefore, the concept of tensor column is introduced. Under the concept of tensor column, the expansion matrix $\chi_{(k)}$ is defined as $\chi_{\lfloor k \rfloor} \in \mathbb{R}^{m\times n}(m = \prod_{l=1}^{k} I_l, n = \prod_{l=k+1}^{N} I_l)$, and the rank r_k of $\chi_{\lfloor k \rfloor}$ is related to min (m, n). Compared with

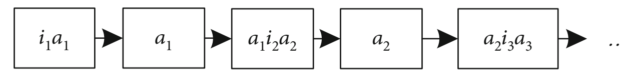


Figure 4: Schematic diagram of tensor column.

Tucker rank, tensor column rank r_k has the advantage of being able to consider the global hidden information of tensor data and is more suitable for describing the relationship between elements in higher-order tensors. Based on this, the low-rank tensor completeness problem defined by formula (4) can be transformed into the form described by formula (5), namely,

$$\min_\chi \sum_{k=1}^{N-1} \alpha_k \left\|\chi_{\lfloor k \rfloor}\right\|_* \text{ s.t.} \chi_\Omega = \tau_\Omega \tag{5}$$

Among them, $\sum_{k=1}^{N-1} \alpha_k \|\chi_{\lfloor k \rfloor}\|_*$ is the tensor kernel column norm, $\sum_{k=1}^{N-1} \alpha_k = 1$..

Based on the above analysis, since tensor column rank can effectively obtain the hidden information of tensor data, a solution to formula (5) is proposed based on the concept of TT-rank. The designed scheme first takes into account the unbalanced information distribution and redundant data information in the streaming media data expressed as a tensor, and the negative impact on the data repair result is adopted. Improved tensor column decomposition is used as an approximate tensor generation mechanism, based on TT-rank is used to obtain a tensor streaming media data with more balanced information distribution and only keeping important information [22]. Second, in order to better map the influence of each dimension of tensor data in the optimization iteration process, the proposed solution proposes an adaptive weighting mechanism based on the rank of the tensor column. Finally, SiLRTC-TT is used to carry the two mechanisms mentioned above to form an adaptive weighted tensor completion algorithm based on TT-rank (AWTC-TT), and the proposed AWTC-TT algorithm is used to realize common distributed sensing equipment. Perceived streaming media data repair is shown in [23].

3.2. Approximate Tensor Solution for Rank of Tensor Column. In the designed streaming media repair algorithm, the unbalanced information distribution and redundant information in the tensor may have a negative impact on the data repair result. Therefore, an approximate tensor solution algorithm is proposed based on tensor column decomposition, and the original data tensor structure is adjusted by TT-rank to obtain tensor data that only retains more important information and has a more balanced information distribution [24]. The introduced approximate tensor solving algorithm can be regarded as an improved version of tensor sequence decomposition.

A tensor column is a form of information expression of a tensor, and the tensor column can be represented as shown in Figure 4.

i_k represents the spatial index. a_k represents the auxiliary index, and i_k is contained. a_k and a_k represent the tensor

Input: tensor $\tau \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}$, tensor column rank $r_{1:i=1,2,\cdots,N-1}$, $r_0 = r_N = 1$
Output: Approximate tensor τ_p of τ
Algorithm description:
1) temporary variables $C = \tau$
2) for $k := 1$ to $(N-1)$
3) reshape C to $\tau_k \in \mathbb{R}^{(r_{k-1}I_k)\times(I_{k+1}\cdots I_N)}$
4) calculate SVD and intercept with r_k, thus
$SVD(\tau_k) = u_k \lambda_k v_k^T$,
$u_k \in \mathbb{R}^{(r_{k-1}I_k)\times r_k}$,
$\lambda_k \in \mathbb{R}^{r_k \times r_k}$,
$v_k \in \mathbb{R}^{r_k \times (I_{k+1}, I_{k+2}, \cdots, I_N)}$
5) $\vartheta^{(k)} = reshape(u_k, [r_{k-1}, I_k, r_k])$
6) $C := \lambda_k v_k^T \in \mathbb{R}^{r_k \times (I_{k+1}, I_{k+2}, \cdots, I_N)}$
7) end for
8) $\vartheta^{(N)} = C$

Algorithm 1: Approximate tensor solving algorithm based on tensor column rank.

column core. If there are auxiliary indexes in the two tensor column kernels, connects the two matrices [25].

For a tensor of order τ, the decomposition of the tensor sequence can be defined in the form of formula (6). Among them, $\vartheta^{(k)}$ represents the tensor kernel. In the tensor column, its rank satisfies $r_k \in r = (r_1, r_2, \cdots, r_{N-1})$, $r_0 = r_N = 1$. Different from tensor column decomposition, in the designed approximate tensor solution scheme, the input streaming media tensor τ does not need to meet the characteristics of the tensor column rank [26].

$$\tau = \vartheta^{(1)}, \vartheta^{(2)}, \cdots, \vartheta^{(N)}. \tag{6}$$

The approximate tensor solution scheme is used to obtain the streaming media data tensor that only retains important information, and the information distribution is more uniform based on the preset better tensor column rank. The approximate tensor solution algorithm introduced is as Algorithm 1. In Algorithm 1, τ is the tensor representing the original streaming media data, and C is a temporary variable. Then, SVD decomposition is performed on the deformation τ_k of C, truncation is completed based on the preset tensor column rank r, and the unitary matrix u_k is redefined to obtain core tensor $\vartheta^{(k)}$. Finally, the approximate tensor τ_p of the original streaming media data is obtained, and the tensor τ_p is used in the subsequent streaming media repair algorithm [27].

4. Adaptive Weighting Mechanism Based on Rank of Tensor Column

The nuclear norms of the expansion matrices of different orders will have different effects in the tensor data restoration process, and α_k can well map the influence of the nuclear norms of the expansion matrices of each order in the restoration process. Based on this, an adaptive weighting mechanism based on the rank of the tensor column is proposed to adjust the value of α_k adaptively to achieve a better repair effect.

4.1. Flow of Adaptive Weighting Algorithm Based on Rank of Tensor Column. In the low-rank tensor completeness problem, the weight α_k measures the influence of the kernel norm of the k-th expansion matrix in the entire repair process, and the kernel norm is similar to the rank of the expansion matrix $\chi_{\lfloor k \rfloor}$ under certain conditions. Therefore, the weight A can be adjusted according to the rank of the expanded matrix. Based on the literature [28], the rank r_k of the expanded matrix $\chi_{\lfloor k \rfloor}$ can be obtained by observing the singular value distribution of $\chi_{\lfloor k \rfloor}$ (where the singular values are arranged in descending order). Based on this, the adaptive adjustment of weight α_k is completed according to the singular value distribution of the expanded matrix.

In the adaptive weight mechanism, the weight satisfies $\sum_k^{N-1} \alpha_k = 1$. Then, arrange the singular values of the expanded matrix $\chi_{\lfloor k \rfloor}$ in descending order: $\delta^{(k)} = [\delta_1^{(k)}, \delta_2^{(k)}, \cdots, \delta_{n_k}^{(k)}]$, where $k = 1, 2, \cdots, N-1$ and n_k refers to the number of singular values of $\chi_{\lfloor k \rfloor}$. In this way, more important singular value elements can be retained. In order to obtain the weight α_k that can effectively reflect the influence of $\chi_{\lfloor k \rfloor}$ in the repair process, the proposed adaptive weighting mechanism first defines the parameter $\rho (0 < \rho < 1)$ to obtain the information ratio of the first g singular value elements in the entire singular value, namely,

$$\rho = \frac{\sum_{i=1}^{g} \delta_i}{\sum_{i=1}^{n_k} \delta_i}. \tag{7}$$

Then, the threshold th is defined so that when ρ satisfies $\rho \geq \text{th}$, the minimum g value is determined and denoted by

Input: tensor $\chi \in \mathbb{R}^{I_1 \times I_2 \times \cdots I_N}$, threshold th
Output: the weight corresponding to each expansion matrix
Algorithm description:
1) for $k := 1$ to $(N-1)$
2) $\chi_{\lfloor k \rfloor} = reshape(\chi, [\prod_{l=1}^{k} I_l, \prod_{l=k+1}^{N} I_l])$
3) calculate $SVD(\chi_{\lfloor k \rfloor})$ to get the singular value, and sort the singular value $\delta^{(k)}$ in descending order
4) Find the smallest g_k according to formula (7) and th
5) According to formula (8), normalize g_k to obtain $\overline{g_k}$
6) According to formula (9), the final weight α_k is obtained
7) end for

Algorithm 2: Adaptive weighting mechanism based on tensor column rank.

Input: tensor $\tau \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}$, known data index set$\Omega$, initial weight α_k, $k = 1, 2, \cdots, N-1$, β_k and initial tensor column rank r
Output: repaired tensor data
Algorithm description:
1) Get the approximate tensor $\tau_p$of τaccording to Algorithm 1
2) initial $\chi^0, \chi^0_\Omega = (\tau_p)_\Omega, l = 0$
3) while the convergence condition is not met
4) for $k := 1$ to $(N-1)$
5) expand $\chi^l$to get the k-th order expansion matrix $\chi^l_{\lfloor k \rfloor}$
6) $M_k^{l+1} = D_{\alpha_k/\beta_k}(\chi^l_{\lfloor k \rfloor})$
7) end for
8) update χ^{l+1} based on M_k^{l+1} according to formula (15)
9) update the weights according to Algorithm 2
10) end while

Algorithm 3: TT-rank-based adaptive weighted tensor completion algorithm (AWTC-TT).

g_k. Then, normalize g_k based on formula (8) to obtain the following:

$$\overline{g_k} = \frac{g_k}{n_k}. \tag{8}$$

Finally, the weight α_k is defined as follows:

$$\alpha_k = \frac{\eta \overline{g_k} / e^{\overline{g_1} + \overline{g_2} + \cdots + \overline{g_{N-1}}}}{\Sigma_i^{N-1} \eta \overline{g_i} / e^{\overline{g_1} + \overline{g_2} + \cdots + \overline{g_{N-1}}}}, k = 1, 2, \cdots, N-1. \tag{9}$$

Among them, η is a constant. The adopted adaptive weighting algorithm based on tensor column rank is shown in Algorithm 2.

4.2. Adaptive Weighted Tensor Completion Algorithm Based on Rank of Tensor Column. Based on SiLRTC-TT, this paper combines the proposed approximate tensor solving algorithm and adaptive weighting mechanism to build an adaptive weighted tensor completion (AWTC-TT) algorithm based on TT-rank, as shown in formula (10).

$$\min_{\chi} : \Sigma_k^{N-1} \alpha_k \left\| \chi_{\lfloor k \rfloor} \right\|_* \text{s.t.} \chi_\Omega = \left(\tau_p\right)_\Omega \tag{10}$$

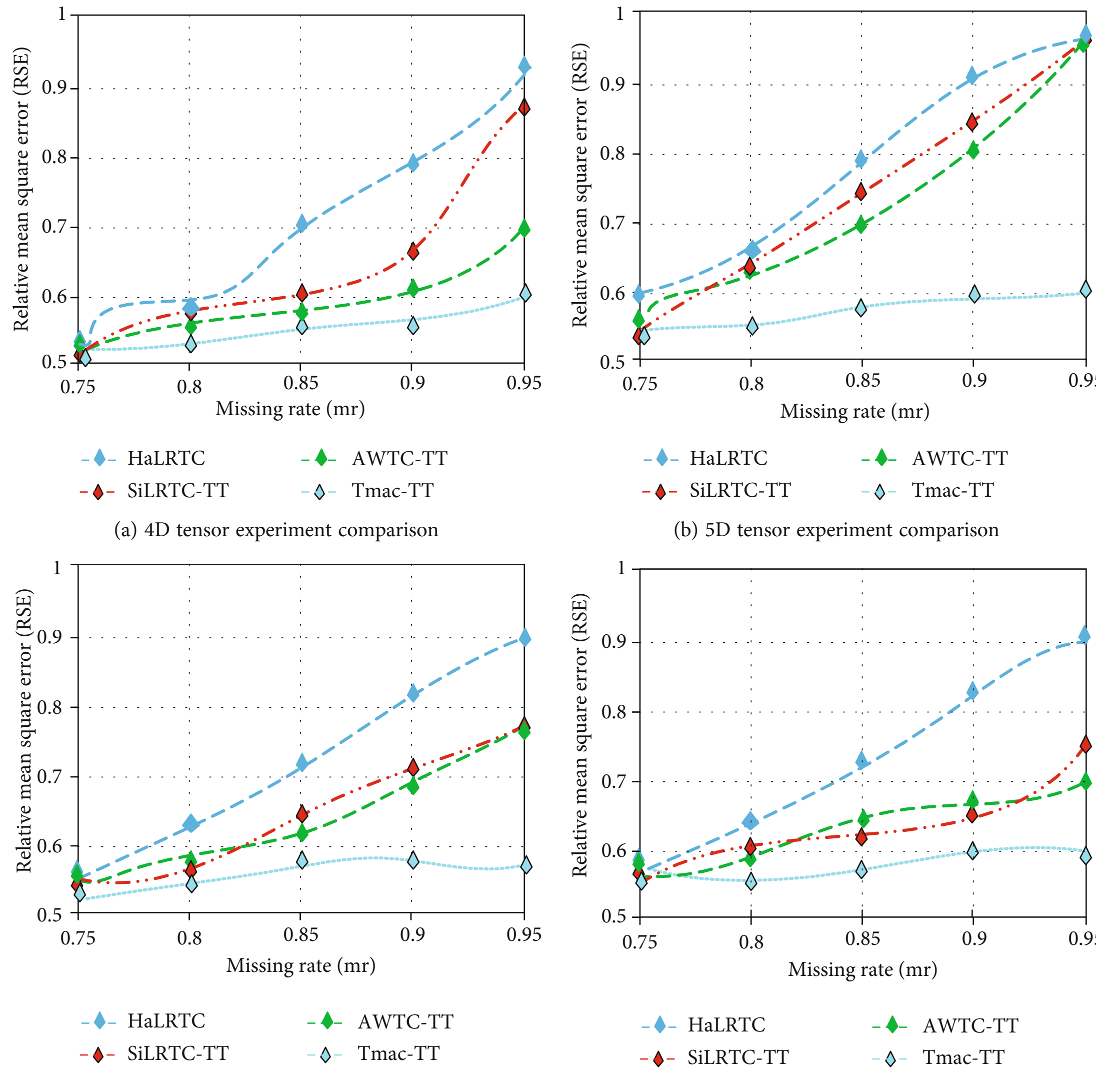
In formula (10), τ_p is obtained by the approximate tensor solving algorithm introduced, and α_k is determined by the adopted adaptive weighting mechanism. Since problem (10) is difficult to solve directly, AWTC-TT introduces matrix $M_1, M_2, \cdots, M_k$ and applies it to formula (10), as shown in formula (11).

$$\begin{aligned} &\min_{\chi, M_k} : \Sigma_k^{N-1} \alpha_k \|M_k\|_* \\ &\text{s.t.} \left\| \chi_{\lfloor k \rfloor} - M_k \right\|_F^2 \le d_k, k = 1, 2, \cdots, N-1 \\ &\chi_\Omega = \left(\tau_p\right)_\Omega. \end{aligned} \tag{11}$$

Among them, $d_k(>0)$ is a custom threshold. Problem (11) can be transformed into the following form in combination with parameter $\beta_k(>0)$:

$$\begin{aligned} &\min_{\chi, M_k} : \Sigma_k^{N-1} \alpha_k \|M_k\|_* + \frac{\beta_k}{2} \left\| \chi_{\lfloor k \rfloor} - M_k \right\|_F^2 \\ &\text{s.t.} \chi_\Omega = \left(\tau_p\right)_\Omega \end{aligned} \tag{12}$$

Then, AWTC-TT uses the Block Coordinate Decent (BCD) method to find the optimal solution to problem (12). Specifically, the variables are divided into matrix M_1, $M_2, \cdots, M_{N-1}$ and tensor χ. If $\chi_{\lfloor k \rfloor}$ is fixed, the calculation



(a) 4D tensor experiment comparison

(b) 5D tensor experiment comparison

(c) 6D tensor experiment comparison

(d) 7D tensor experiment comparison

FIGURE 5: Contrast experiment based on artificial data.

of matrix M_k is related to the optimization problem described by formula (13). Therefore, the optimal closed solution of problem (13) can be obtained by formula (14).

$$\min_{M_k} : \alpha_k \|M_k\|_* + \frac{\beta_k}{2}\left\|\chi_{\lfloor k\rfloor} - M_k\right\|_F^2 \tag{13}$$

$$M_k = D_{\gamma k}\left(\chi_{\lfloor k\rfloor}\right). \tag{14}$$

Among them, $\gamma k = \alpha_k/\beta_k, D_{\gamma k}(\chi_{\lfloor k\rfloor})$ is the thresholded SVD of $\chi_{\lfloor k\rfloor}$, namely, $D_{\gamma k}(\chi_{\lfloor k\rfloor}) = u\lambda_{\gamma k}v^T$, $\lambda_{\gamma k} = \mathrm{diag}\,(\max(\lambda_l - \gamma k, 0))$. After updating the matrix M_k, the optimal χ can be obtained in the following way:

$$\chi_{i_1,\cdots,i_N} = \begin{cases} \left(\dfrac{\Sigma_{k=1}^N \beta_k fold(M_k)}{\Sigma_{k=1}^N \beta_k}\right)_{i_1\cdots i_N} & i_1 \cdots i_N \notin \Omega, \\ (\tau_p)_{i_1\cdots i_N} & i_1 \cdots i_N \in \Omega. \end{cases} \tag{15}$$

The algorithm flow of AWTC-TT is shown in Algorithm 3. In Algorithm 3, the tensor τ represents streaming media data with data missing problems. α_k is the initial weight, which is adjusted according to the proposed adaptive weighting mechanism in the iterative process. r represents the rank of the initial tensor column, which is used in the approximate tensor solving algorithm described in Algorithm 1 to obtain an approximate tensor τ_p that retains only important information and has a more balanced data distribution [29]. Through the iterative process described in Algorithm 3, the repair of the tensor τ with the data missing problem can be completed.

5. Experiment and Result Analysis

Based on artificial data, color picture streaming media data, and actual monitoring scene perception streaming media data, this paper completes the performance verification of the proposed algorithm AWTC-TT and completes the comparison with HaLRTC, SiLRTC, SiLRTC-TT, and on the

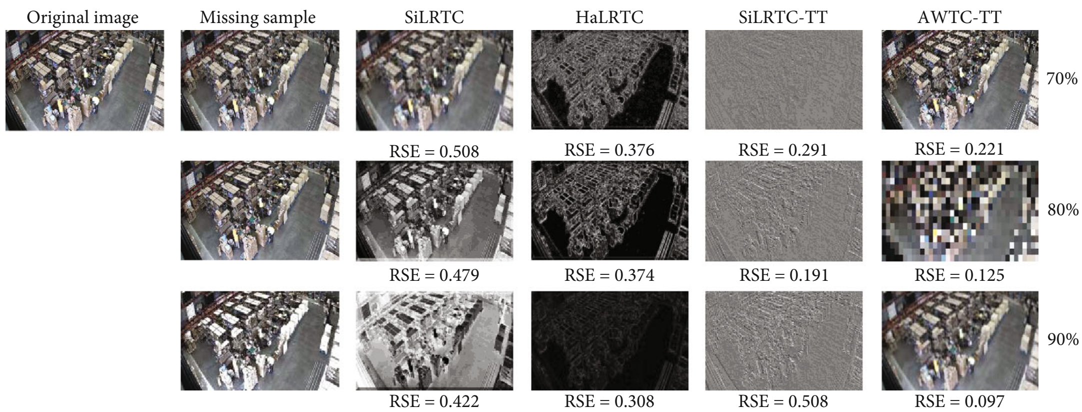


FIGURE 6: Comparison of experimental results based on "Lena."

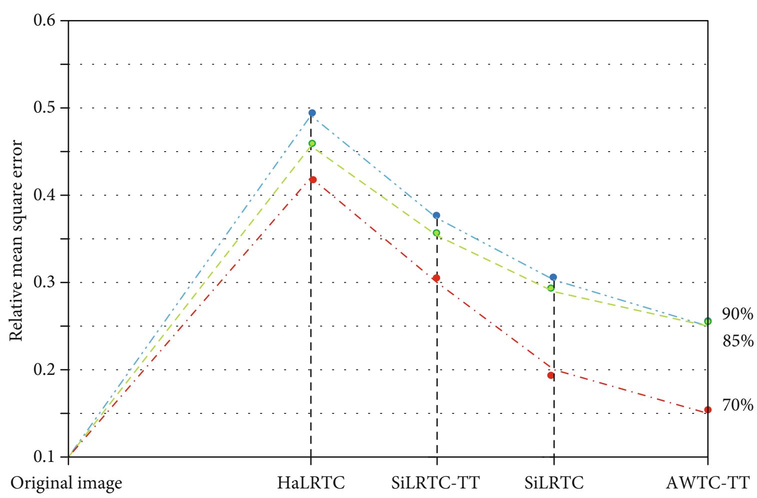


FIGURE 7: Comparison of experimental results based on "Baboon."

public data set. Performance comparison of TNN and TMAC-TT algorithms.

5.1. Experimental Algorithm Settings. The designed experiments are all carried out under the assumption that the experimental data is low-rank. KA refers to the ket augmentation, which is used in experiments to obtain high-order low-dimensional data [30].

5.2. Experimental Platform Construction. The experiment was carried out in the MatLab environment, running on the hardware platform of Intel(R)CoreTM, i5-10500 processor with 32 GB memory. In the experiment, experimental data with different missing ratios (mr) were used to complete the performance verification of AWTC-TT. The missing rate is represented by formula (16), where P represents missing data, which is randomly selected from the original tensor data based on a uniform distribution.

$$\mathrm{mr} = \frac{P}{\Pi_{k=1}^{N} I_k}. \quad (16)$$

The initial weights in the algorithms HaLRTC, SiLRTC, and SiLRTC-TT are determined by formulas (17) and (18), respectively.

$$\alpha_k = \frac{I_k}{\Sigma_{k=1}^{N} I_k}, \quad (17)$$

$$\alpha_k = \frac{\sigma_k}{\Sigma_{k=1}^{N-1}\sigma_k}, \sigma_k = \min\left(\Pi_{l=1}^{k} I_l, \Pi_{l=k+1}^{N} I_l\right). \quad (18)$$

In the TMAC-TT algorithm, the initial rank r_k is obtained by singular values satisfying the following inequalities. Among them, $\{\delta_j^{[k]}\}$ is the nonzero singular value in descending order, $j = 1, 2, \cdots, r_k$, and T is the threshold.

$$\frac{\delta_j^{[k]}}{\delta_1^{[k]}} > T. \quad (19)$$

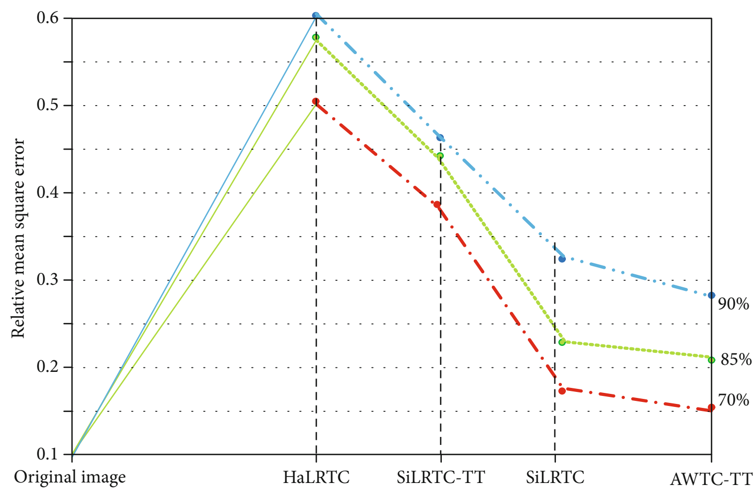


Figure 8: Comparison of experimental results based on "Peppers."

Table 1: Comparison results of RSE for 70% deletion rate.

	Lena	Peppers	Baboon
SiLRTC	0.4227	0.5067	0.3966
HaLRTC	0.2903	0.3666	0.2793
SiLRTC-TT	0.1197	0.1632	0.1732
TMAC-TT+KA	0.0813	0.0982	0.1342
TMAC-TT+KA_in	0.1795	0.2914	0.2610
TMAC-TT	0.1134	0.1997	0.1643
TMAC-TT_in	0.2352	0.3399	0.2151
AWTC-TT	0.1009	0.1344	0.1385
AWTC-TT_inM	0.1105	0.1382	0.1563

For the AWTC-TT algorithm, the experiment sets the initial weight to the following:

$$\alpha_k = \frac{r_k}{\sum_{k=1}^{N-1} r_k}. \tag{20}$$

Among which, $k = 1, 2, \cdots, N-1$, r_k is the optimal tensor rank obtained from experience. In the subsequent iterative optimization process, the adaptive weight mechanism is used to update α_k. In the experiment, when threshold value th in Algorithm 2 is in the range of [0.85,0.98], $\eta = 500$. For $\beta_k(>0)$, by decision of $\beta_k = f\alpha_k$, f is the empirical value, set to 1.05. The convergence factor used in the iterative optimization process is defined as follows:

$$\varepsilon = \frac{\|\chi^{l+1} - \chi^l\|_F}{\|\tau\|_F} \le eps. \tag{21}$$

Among them, $\|\chi^{l+1} - \chi^l\|_F$ is the relative error of tensor χ, and $eps = 10^{-4}$, and in the experiment, the maximum number of iterations is set to 2000.

Table 2: Comparison results of RSE for 90% deletion rate.

	Lena	Peppers
SiLRTC-TT+KA	0.148	0.208
AWTC-TT	0.224	0.289

The experiment uses relative mean square error (RSE) as a measure of the repair effect, as shown in formula (22):

$$\text{RSE} = \frac{\|\chi - \tau\|_F}{\|\tau\|_F}. \tag{22}$$

5.3. Experimental Results and Analysis Based on Public Data Sets

(1) Experimental Results and Analysis Based on Artificial Data

First, manual data is used to verify the repair performance of AWTC-TT. The experimental tensor data are 4D $20 \times 20 \times 20 \times 20$, 5D $30 \times 5 \times 5 \times 5 \times 5$, 6D $30 \times 5 \times 5 \times 5 \times 5 \times 5$, and 7D $30 \times 5 \times 5 \times 5 \times 5 \times 5 \times 5$. The performance of AWTC-TT was verified by artificial data with 95%, 90%, 80%, and 70% information loss rate and compared with haltc, sirtc TT, and TMAC-TT.

The experimental comparison results based on artificial data are shown in Figure 5.

According to the analysis of Figure 5, AWTC-TT has the suboptimal repair performance. Specifically, the relative mean square error RSE of AWTC-TT is lower than that of HaLRTC. With the increase of the tensor order, AWTC-TT can have better performance than SiLRTC-TT when the loss rate is up to 95%. However, the relative mean square error RSE of AWTC-TT is higher than TMAC-TT algorithm, which has a certain performance gap with TMAC-TT algorithm. In the experiment of artificial data, the artificial data used are not identical, and the experimental results of different levels of artificial data are not compared with the experiments.

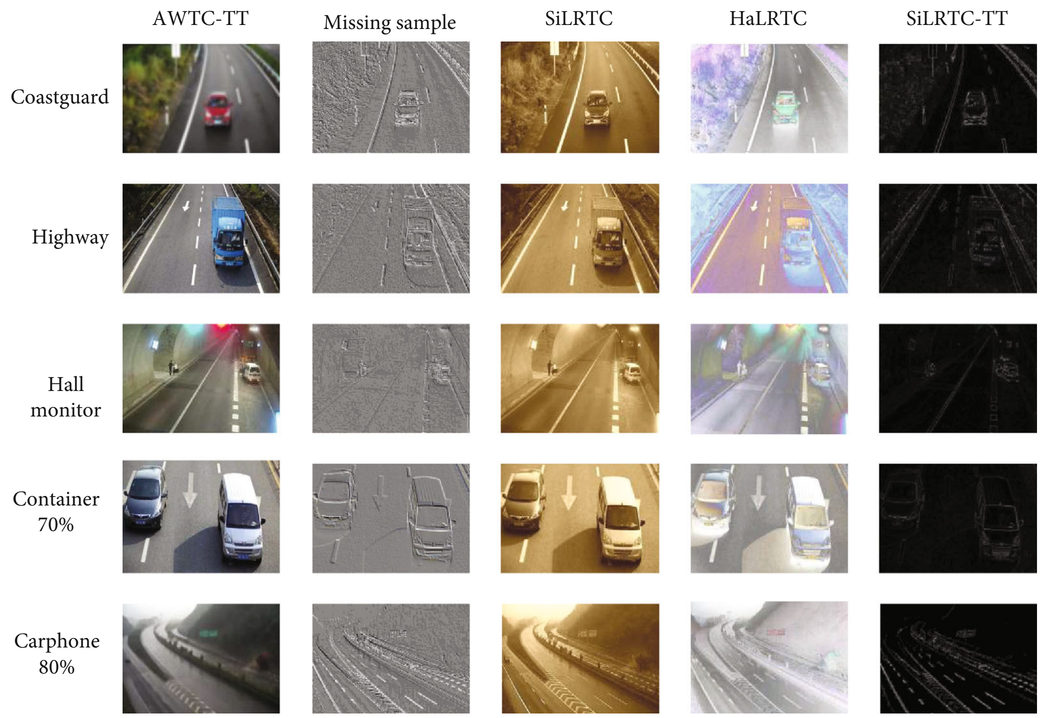


FIGURE 9: Experimental results of color streaming media based on 90% missing rate.

(2) Experimental results and analysis based on color images

Second, the color images "Lena," "Baboon," and "Peppers" in public image data set are used to verify the repair performance of AWTC-TT algorithm, and the repair results are compared with those of SiLRTC, HaLRTC, SiLRTC-TT, and TMAC-TT. In the experiment, color images are transformed into third-order tensor $512 \times 512 \times 3$ (image_width $\times$ image_height $\times$ channel), that is $\tau \in \mathbb{R}^{512\times512\times3}$. In the experiment based on color pictures, in order to complete the comparative experiment with TMAC-TT, the experimental data is expressed in the form of image $\tau \in \mathbb{R}^{256\times256\times3}$.

The experimental results based on "Lena" $512 \times 512 \times 3$ are shown in Figure 6.

The original column in Figure 6 shows the original data, and the missing sample column shows the sample graph obtained according to the missing rate. The columns of SiLRTC, HaLRTC, SiLRTC-TT, and AWTC-TT, respectively, present the repaired images obtained by corresponding algorithms. According to the analysis of Figure 6, the performance of AWTC-TT is better than that of SiLRTC, HaLRTC, and SiLRTC-TT. Specifically, SiLRTC algorithm can only simply give the structure of the original image, especially when the missing rate $mr \geq 80\%$. SiLRTC algorithm has the worst repair performance. Compared with SiLRTC, hallrtc can get better results, but there is still a gap between hallrtc and SiLRTC-TT. Compared with other algorithms, AWTC-TT can get a clearer repair image. Although the repair result of $mr \geq 80\%$ has no obvious advantage, the relative mean square error in Figure 6 can well reflect the performance superiority of the proposed streaming media repair algorithm compared with other algorithms.

The experimental results based on Baboon $512 \times 512 \times 3$ are shown in Figure 7.

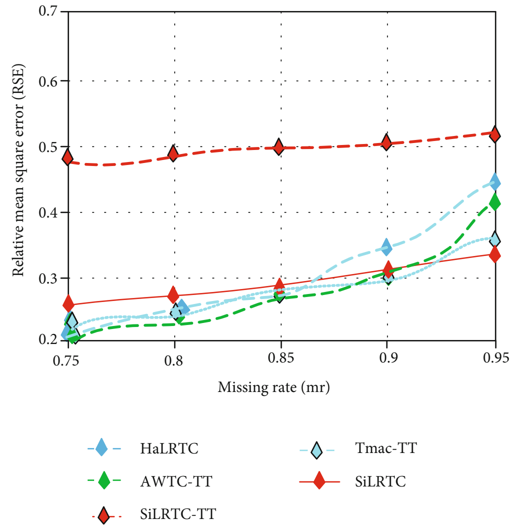
The repair results in Figure 7 show the effectiveness of AWTC-TT. The repaired image of SiLRTC algorithm has the lowest similarity with the original image. The repair effect of HaLRTC is better than that of SiLRTC. The repaired images of SiLRTC-TT and AWTC-TT have the highest similarity with the original image. Compared with the SiLRTC-TT algorithm, AWTC-TT has better repair effect in texture and color, and AWTC-TT has the lowest relative mean square error $RSE = 0.160$. That is to say, on the other hand, it shows the effectiveness of the proposed streaming media repair method based on tensor rank.

The experimental results and experimental comparison results based on "Peppers" of $512 \times 512 \times 3$ are shown in Figure 8.

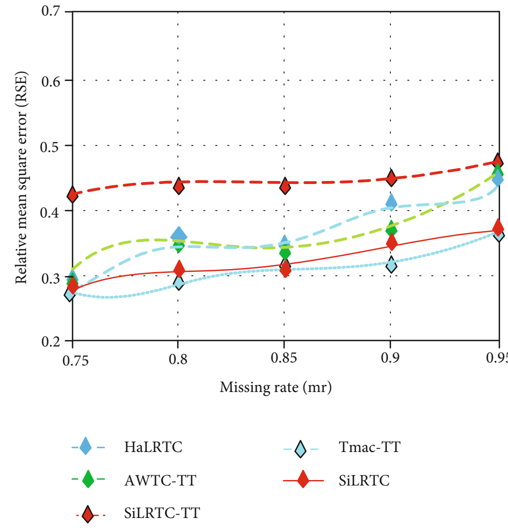
Experiments show that SiLRTC and HaLRTC algorithms have relatively poor repair performance. Although the AWTC-TT algorithm has no obvious advantage over the SiLRTC-TT algorithm in image restoration, the designed scheme achieves the lowest relative mean square error in the case of high loss rate, which verifies the performance improvement of AWTC-TT to a certain extent.

At the same time, the experiment uses images with a size of $256 \times 256 \times 3$ of "Lena," "Baboon," and "Peppers" to complete the comparative experiment with TMAC-TT. Table 1 shows the relative mean square error comparison results of the deletion rate $mr = 70\%$.

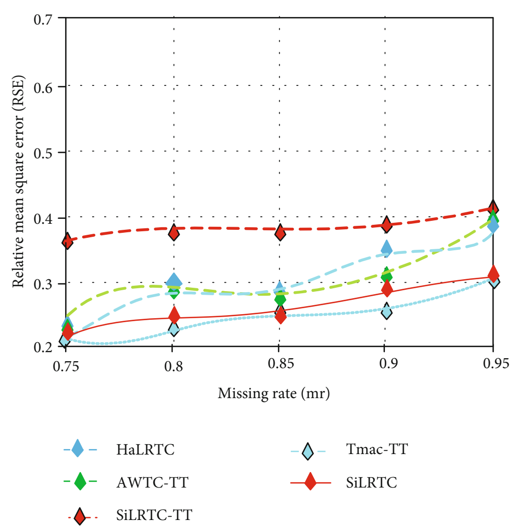
In Table 1, TMAC-TT represents the experimental results without using tensor enhancement (KA). TMAC-TT+KA is the experimental results under the condition of



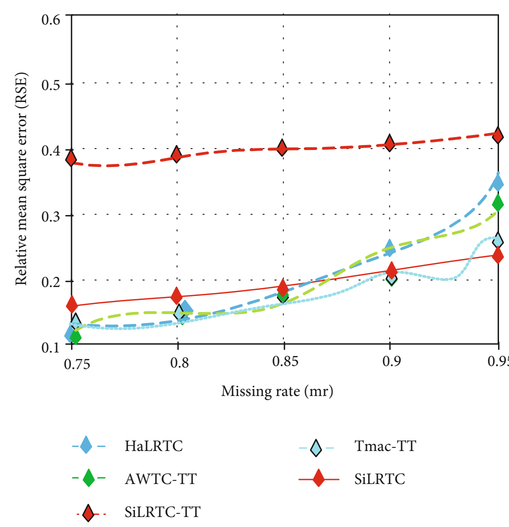
(a) Coastguard



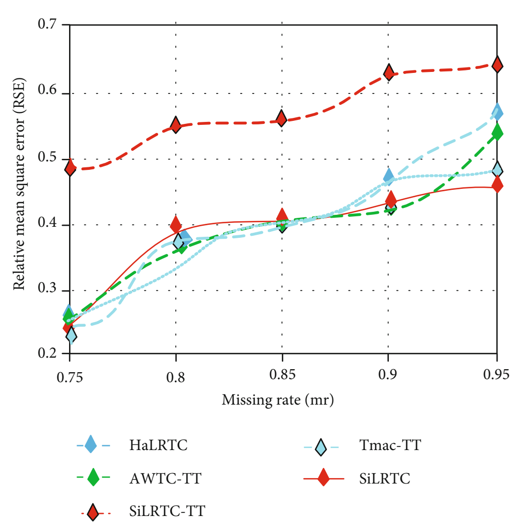
(b) Highway



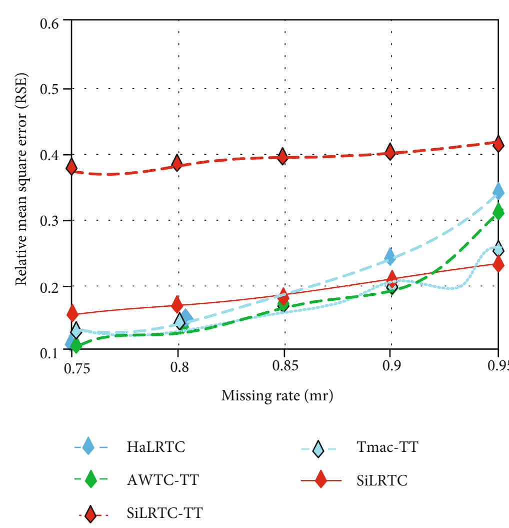
(c) Hall Monitor



(d) Container



(e) Salesman



(f) Carphone

Figure 10: Comparison results of relative mean square error based on color streaming media with different loss rates.

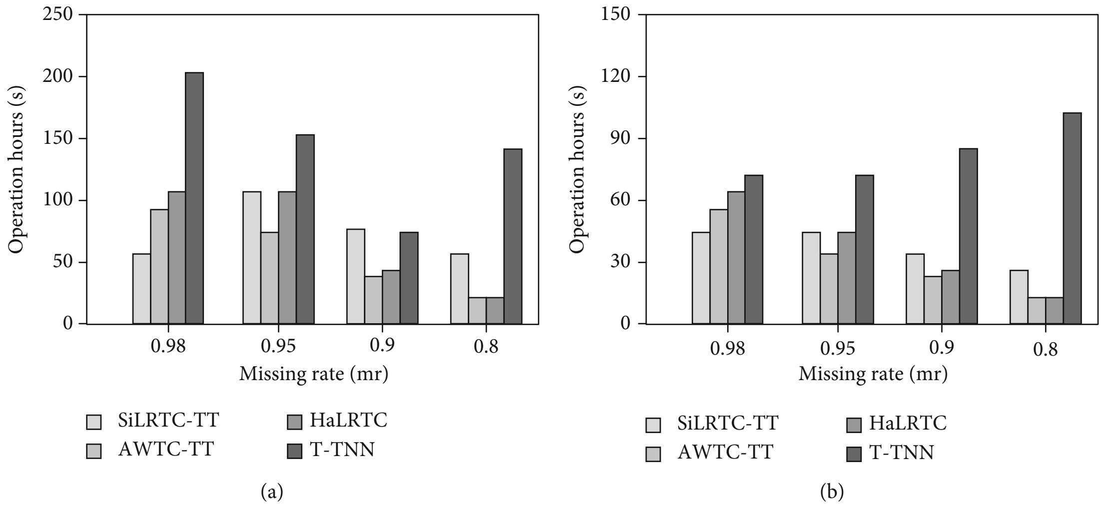


Figure 11: Comparison of repair time of streaming media.

Table 3: Comparison results of RSE based on “Bus” and “New York City” with 90% deletion rate.

	Bus	New York City
AWTC-TT	0.362	0.164
TMAC-TT+KA	0.092	0.066

Table 4: Average RSE results of validation experiment of approximate tensor solving algorithm.

	98%	95%	90%
AWTC-TT	0.3151	0.1567	0.1074
AWTC-TT no. S1	0.3190	0.1593	0.1092

using KA. In order to better verify the performance of the proposed algorithm, the experiments design the comparison experiments based on the missing rate sampling method and TMAC-TT loss rate sampling method.

Therefore, in Table 1, TMAC-TT+KA_in is the result of TMAC-TT method using KA, which is the sampling method in this paper_in is the experimental results of the method of sampling in this paper without KA. AWTC-TT_inM is the experimental result of AWTC-TT which combines the sampling method in TMAC-TT. It can be seen from the experimental results that the lowest RSE results are obtained by using KA operated TMAC-TT, but in the sampling method of this experiment, TMAC-TT+KA_in effect is not as good as AWTC-TT. In contrast, AWTC-TT can obtain better results both in the sampling method and TMAC-TT sampling method. Therefore, the results show that AWTC-TT has better repair performance than SiLRTC, HaLRTC, and SiLRTC-TT; compared with TMAC-TT algorithm, the proposed algorithm has the advantage of stability. Table 2 shows the experimental results of sirrtc TT algorithm combined with tensor enhancement algorithm. From the experimental results, AWTC-TT results are slightly inferior to the SiLRTC-TT algorithm with tensor enhancement.

(3) Experimental results and analysis based on color streaming media

Furthermore, the performance of AWTC-TT is verified by using the color streaming media data in the public dataset: “Coastguard,” “Hall Monitor,” “Salesman,” “Highway,” “Carphone,” and “Container.” In the experiment using color streaming media, the streaming media sequence is first transformed from YUV format to RGB format and expressed as a 4th-order tensor $\tau \in \mathbb{R}^{176\times144\times3\times50}$ (frame_height × frame_width × RGB × frames) form.

The repair results of color streaming media based on different missing rate (mr) are shown in Figure 9.

Figure 9 shows the experimental comparison results of relative mean square error (RSE). From the experimental results, we can see that AWTC-TT has better repair performance than other algorithms, and even in the case of high loss rate ($\mathrm{mr} \geq 95\%$), it still has good repair performance.

In the case of high missing rate ($\mathrm{mr} \geq 95\%_{),}$ SiLRTC-TT and TMAC-TT algorithms have relatively better repair performance, and TMAC-TT algorithm has the lowest relative mean square error when $\mathrm{mr} = 98\%$, but from the overall effect, the repair streaming media frame image of the proposed streaming media repair scheme is the best in vision.

The motion of “Highway” streaming media sequence is relatively stable, and AWTC-TT presents the best repair effect. Through the analysis of the repair results, it can be seen that HaLRTC algorithm and SiLRTC-TT algorithm can only repair the general structure of the original streaming media frame when the loss rate is higher than 95% ($\mathrm{mr} \geq 95\%$). Although TMAC-TT achieved highly competitive results with a deletion rate of 98%, but the proposed streaming media repair mechanism has better performance in details. The RSE results of “Highway” streaming media sequence are presented.

The relative mean square error comparison results of color streaming media with different loss rates are shown in Figure 10.

In the “Hall Monitor” streaming media sequence, the background is still and remains unchanged. In the situation

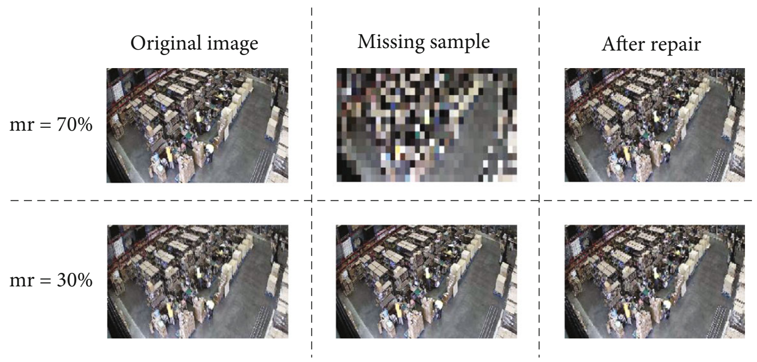


Figure 12: Repair results based on "SYQ."

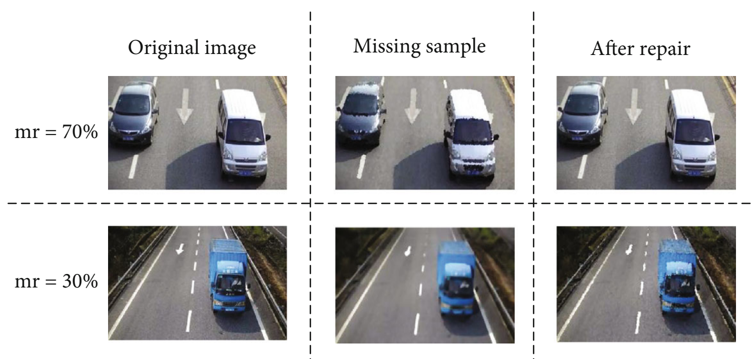


Figure 13: Repair results based on "QJJ."

of missing rate (mr $\geq 95\%\sqrt{b^2 - 4ac}$), HaLRTC and TMAC-TT algorithms have relatively poor repair effect. SiLRTC-TT algorithm is used to repair the disordered texture in streaming media frames. Repair mechanism can get clear repair streaming media frame. By comparing the results of RSE shown in Figure 10(c), the RSE broken line of AWTC-TT algorithm is always lower than that of other algorithms, indicating the superiority of AWTC-TT.

There are several moving objects in the "Container" streaming media sequence, and they have different motion states. In the case of high loss rate, HaLRTC and TMAC-TT can only repair the basic architecture of the original streaming media frame. SiLRTC-TT has relatively good performance, but AWTC-TT can get the best quality repair streaming frames when the loss rate is 98%, 95%, and 90%. According to the observation of RSE comparison results shown in Figure 10(d), although TMAC-TT obtains the lowest relative mean square error when the deletion rate is 98%, the proposed streaming media repair algorithm AWTC-TT shows better performance on the whole.

The background of "Salesman" streaming media sequence is static, while the background of "Carphone" streaming media sequence is fast changing. AWTC-TT cannot repair the facial information in "Salesman" and "Carphone" well in the situation of high deletion rate. But compared with HaLRTC, SiLRTC-TT, and TMAC-TT, AWTC-TT has better repair performance. Through the analysis of the experimental comparison results of relative mean square error shown in Figures 10(e) and 10(f), it can be seen that the RSE value of AWTC-TT algorithm is lower than that of the comparison algorithm, which verifies the performance improvement of AWTC-TT to a certain extent.

The experimental comparison results of loss rate of streaming media "Bus" and "New York City" mr = 90% are shown in Table 3.

TMAC-TT+KA represents the experimental results of the data enhancement method in TMAC-TT sampling method. Through the analysis of the experimental results, AWTC-TT needs to be further improved to better play the advantages of the rank of tensor to further improve the repair performance.

In this paper, experiments are designed to verify the effectiveness of Algorithm 1 to describe the approximate tensor generation algorithm. The experimental results are shown in Table 4.

Through the analysis of the experimental results, it can be seen that the proposed approximate tensor generation algorithm has a positive effect on getting high-quality repair streaming media data.

(4) Run time analysis

The average processing time based on color streaming media is shown in Table 5, and the running time comparison results of "Coastguard" and "Hall Monitor" are shown in Figure 11.

The experimental results show that the running time of AWTC-TT does not increase significantly because of the approximate tensor solving algorithm and weight updating

Table 5: Average running time based on color streaming media (streaming media/s).

	98%	95%	90%	85%
HaLRTC	31.8000	35.1023	34.7449	33.0983
SiLRTC	40.3557	13.9766	9.2721	5.2973
t-TNN	70.0655	74.0023	71.9478	69.3748
SiLRTC-TT	52.2170	26.8742	20.4500	13.5870
AWTC-TT	60.5685	33.3552	22.4088	14.3482

mechanism. Compared with t-TNN, AWTC-TT has some advantages. However, compared with SiLRTC algorithm, it still needs further optimization. Because t-TNN cannot deal with the fourth-order tensor directly, it is necessary to transform the fourth-order tensor into the third-order tensor in the experiment of t-TNN.

Compared with SiLRTC, HaLRTC, SiLRTC-TT, and TMAC-TT algorithms, AWTC-TT algorithm shows competitive repair performance in both manual data and color image streaming data. Second, the calculation time of AWTC-TT does not increase significantly because of the strategy to improve the repair effect.

However, AWTC-TT algorithm still has some limitations. First of all, AWTC-TT cannot repair the facial details such as “Salesman” and “Carphone” in the case of high deletion rate. Second, the processing time of AWTC-TT needs to be further improved. Finally, AWTC-TT needs to be further optimized to give full play to the advantage of tensor rank, so as to further improve the repair performance.

5.4. Experimental Results and Analysis Based on Actual Monitoring Scene Perception Data. Based on the actual monitoring data “SYQ” and “QJJ” sensed by common sensing devices, the repair performance of the proposed algorithm AWTC-TT is verified. The experimental results are shown in Figures 12 and 13. The results show that AWTC-TT can effectively repair the missing data in perceptual streaming media.

The target motion in the monitoring environment perception data “SYQ” is violent and has some deformation. From the repair results of perceptual data with different loss rates shown in Figure 12, it can be seen that compared with the original streaming media frame, AWTC-TT’s repair results can recover the missing information of perceptual streaming media data more completely, although some color information is missing. AWTC-TT can recover the missing information of perceptual data according to the known data even in the situation of 70% missing information of perceptual data, so as to improve the quality of perceptual streaming media.

The target in the monitoring environment perception data “QJJ” has similar characteristics to the monitoring environment, and the target has certain deformation due to the movement. From the repair results in different loss rates shown in Figure 13, it can be seen that AWTC-TT can completely recover the missing information in the perceptual streaming media data. When the missing rate is 70%, AWTC-TT algorithm can estimate the missing information of perceptual data according to the existing data, so as to improve the quality of perceptual streaming media.

6. Conclusion

To solve the problem of obtaining valuable target information based on common sensing devices, aiming at the problem of data quality degradation caused by the limitations of common sensing devices in the sensing streaming media acquisition module, this paper studies the sensing optimization scheme based on the streaming media repair algorithm, The TT-rank adaptive weighted tensor completion algorithm (AWTC-TT) is proposed to complete the repair of streaming media data with missing information. Experimental results show that the proposed algorithm has competitive repair performance compared with existing algorithms. The main results of this paper are as follows:

(1) An algorithm based on the adaptive weighted tensor completion algorithm is proposed to complete the repair of streaming media data perceived by the ordinary sensing devices

(2) According to the known data information, the algorithm in this paper can improve the quality of perceptual streaming data by 3% and maintain the advantage of 2% in average processing time

(3) The AWTC-TT algorithm can estimate the missing information of the perceptual data according to the existing data to improve the quality of perceptual streaming media

For the problem of data quality degradation caused by the limitations of common sensing devices, the tensor-based streaming media repair algorithm can effectively alleviate the missing problem of data degradation. However, the proposed algorithm is based on the assumption that streaming media data is low rank. In practical applications, the perceptual streaming media data does not always meet the low-rank condition, so it is necessary to carry out further research on the low-rank repair scheme.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors’ Contributions

The authors of the manuscript “Perceived Integrity of Distributed Streaming Media Based on AWTC-TT Algorithm Optimization” declare the following contributions to the creation of the manuscript: Wenwu Yu: conceptualization, resources, methodology, and writing; Peng Xu: supervision and project administration; Yue Zhai: original draft and writing—review and editing; and Jingjing Jiang: resources and review.

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References

[1] A. Neuhauser and J. Stavropoulos, *Audio matching with semantic audio recognition and report generation*, The Nielsen Company (Us), Llc, 2017.

[2] N. Holighaus, G. Koliander, Z. Průša, and L. D. Abreu, "Characterization of analytic wavelet transforms and a new phaseless reconstruction algorithm," *IEEE Transactions on Signal Processing*, vol. 67, no. 15, pp. 3894–3908, 2019.

[3] J. A. Bengua, H. N. Phien, H. D. Tuan, and M. N. Do, "Efficient tensor completion for color image and video recovery: low-rank tensor train," *IEEE Transactions on Image Processing*, vol. 26, no. 5, pp. 2466–2479, 2017.

[4] W. T. Qiu, J. Zhao, and J. Liu, "Image matching algorithm combining SIFT with region segmentation," *Chinese Journal of Liquid Crystals and Displays*, vol. 27, no. 6, pp. 827–831, 2012.

[5] W. Hu, D. Tao, W. Zhang, Y. Xie, and Y. Yang, "The twist tensor nuclear norm for video completion," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 12, pp. 2961–2973, 2017.

[6] C. Hima, M. Baburaj, and S. N. George, "A novel technique to remove marked dynamic object from video based on reweighted low rank tensor completion," in *2018 IEEE 3rd International Conference on Computing, Communication and Security (ICCCS)*, pp. 25–29, Kathmandu, Nepal, 2018.

[7] Y. Chen and Y. Zhou, "Total variation regularized low-rank tensor approximation for color image denoising," in *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 2523–2527, Miyazaki, Japan, 2018.

[8] Y. Nie, L. Chen, H. Zhu, S. du, T. Yue, and X. Cao, "Graph-regularized tensor robust principal component analysis for hyperspectral image denoising," *Applied Optics*, vol. 56, no. 22, pp. 6094–6102, 2017.

[9] P. Tokmakov, K. Alahari, and C. Schmid, "Learning motion patterns in videos," in *The Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3386–3394, Honolulu, HI, USA, 2017.

[10] S. Li, B. Seybold, A. Vorobyov, A. Fathi, Q. Huang, and C. C. Kuo, "Instance embedding transfer to unsupervised video object segmentation," in *The Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 6526–6535, Salt Lake City, UT, USA, 2018.

[11] V. Goel, J. Weng, and P. Poupart, "Unsupervised video object segmentation for deep reinforcement learning," *Neural Information Processing Systems*, vol. 11, pp. 5688–5699, 2018.

[12] H. Song, W. Wang, S. Zhao, J. Shen, and K. M. Lam, "Pyramid dilated deeper ConvLSTM for video salient object detection," in *The European Conference on Computer Vision*, pp. 744–760, Springer, Cham, 2018.

[13] V. Jampani, R. Gadde, and P. V. Gehler, "Video propagation networks," in *The Conference on Computer Vision and Pattern Recognition*, pp. 451–461, Honolulu, HI, USA, 2017.

[14] T. Xie, S. Li, L. Fang, and L. Liu, "Tensor completion via nonlocal low-rank regularization," *IEEE Transactions on Cybernetics*, vol. 49, no. 6, pp. 2344–2354, 2019.

[15] I. Kajo, N. Kamel, Y. Ruichek, and A. S. Malik, "SVD-based tensor-completion technique for background initialization," *IEEE Transactions on Image Processing*, vol. 27, no. 6, pp. 3114–3126, 2018.

[16] Y. Qiaoling, L. Xinsong, C. Zheng, and Z. Tingting, "Design and implementation of a distributed parallel system based on streaming media distributing system," *Computer Application*, no. 3, pp. 38–60, 2008.

[17] S. Fatahi and N. G. Aghaee, "Design and implementation of an intelligent educational model based on personality and learner's emotion[J]," *International Journal of Computer ence & Information Security*, vol. 7, no. 3, pp. 30–54, 2010.

[18] L. Li, F. Jiang, and R. Shen, "Total variation regularized reweighted low-rank tensor completion for color image inpainting," in *2018 25th IEEE International Conference on Image Processing (ICIP)*, pp. 2152–2156, Athens, Greece, 2018.

[19] Y. Wang, X. A. Chen, Z. Han, and S. He, "Hyperspectral image super-resolution via nonlocal low-rank tensor approximation and total variation regularization," *Remote Sensing*, vol. 9, no. 12, p. 1286, 2017.

[20] Z. Shen and H. Sun, "Iterative adaptive nonconvex low-rank tensor approximation to image restoration based on ADMM," *Journal of Mathematical Imaging and Vision*, vol. 61, no. 5, pp. 627–642, 2019.

[21] W. Wang, H. Song, S. Zhao et al., "Learning unsupervised video object segmentation through visual attention," in *The Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3064–3074, Long Beach, CA, USA, 2019.

[22] H. Xiao, J. Feng, G. Lin, Y. Liu, and M. Zhang, "MoNet: deep motion exploitation for video object segmentation," in *The Conferenceon Computer Vision and Pattern Recognition (CVPR)*, pp. 1140–1148, Salt Lake City, UT, USA, 2018.

[23] J. Luiten, P. Voigtlaender, and B. Leibe, "PReMVOS: proposal-generation, refinement and merging for video object segmentation," in *TheAsian Conference on Computer Vision (ACCV)*, pp. 565–580, Springer, 2019.

[24] L. Yang, Y. Wang, X. Xiong, J. Yang, and A. K. Katsaggelos, "Efficient video object segmentation via network modulation," in *The Conferenceon Computer Vision and Pattern Recognition (CVPR)*, pp. 6499–6507, Salt Lake City, UT, USA, 2018.

[25] S. W. Oh, J.-Y. Lee, K. Sunkavalli, and S. J. Kim, "Fast video object segmentation by reference-guided mask propagation," in *The Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 7376–7385, Salt Lake City, UT, USA, 2018.

[26] J. Cheng, Y.-H. Tsai, W.-C. Hung, S. Wang, and M.-H. Yang, "Fast and accurate online video object segmentation via tracking parts," in *The Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 7415–7424, Salt Lake City, UT, USA, 2018.

[27] H. Lee, J. Ryu, and J. Lim, "Joint object tracking and segmentation with independent convolutional neural networks," in *The 1st Workshop and Challengeon Comprehensive Video Understanding in the Wild*, pp. 7–13, Seoul Republic of Korea, 2018.

[28] Q. H. Van, L. D. T. Hue, V. D. Du, V. N. Hong, and X. HoangVan, "Complexity controlled side information creation for distributed scalable video coding," in *The International Conference on Recent Advances in Signal Processing,Telecommunications and Computing (Sig Tel Com)*, pp. 104–108, Hanoi, Vietnam, 2019.

[29] Z. Wang, J. Jin, T. Liu et al., "Understanding human activities in videos: a joint action and interaction learning approach," *Neurocomputing*, vol. 321, no. 10, pp. 216–226, 2018.

[30] Q. Wang, L. Zhang, L. Bertinetto, W. Hu, and P. H. S. Torr, "Fast online object tracking and segmentation: a unifying approach," in *The Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1328–1338, Long Beach, CA, USA, 2019.