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Using Analytic Hierarchy Process to Assess Network Video Quality

Zhiming Shi[1,2*], Chengti Huang[1,2], Jianeng Tang[1,2]

[1] College of Engineering, Huaqiao University, Quanzhou Fujian 362021, China

[2] Fujian Provincial Academic Engineering Research Centre in Industrial Intellectual Techniques and Systems, Huaqiao University, Quanzhou Fujian 362021, China
szm_2007@126.com

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Abstract. Nowadays, people watch network video everywhere. Network video has become hot service of Internet. However, many factors may impair the network video quality. The video quality of experience (QoE) is difficult to define. The research of video quality assessment has become a hot topic for service providers. But the objective assessment method is unsure and needs a lot of work. This paper proposes a comprehensive objective assessment method of network quality based on analytic hierarchy process (AHP). The method considers quality of content (QoC), quality of terminal (QoT) and quality of service (QoS) as impair factor. Firstly all the impair factors are extracted and preprocessed. Secondly they are analyzed and optimized by correlation coefficient (CC) and principal component analysis (PCA). This step can find which factors have more close relationship with the video quality and reduce the redundant factor. Thirdly the AHP is used to measure the weight of optimized impair factors. Lastly the proposed method is constituted of different impair factors and gives the objective scores. This method has many advantages: 1. Many factors are considered in a method, such as video parameters, network parameters and performance of terminal. This method is more comprehensive. 2. The extraction of parameters has been optimized by CC and PCA to reduce the dimension. The factors are more concise and clear. 3. The use of AHP is an innovation in this domain. It can effectively establish the mapping relationship between the impair factors and QoE, and get accurate objective results. Meanwhile it can adjust the weight to improve the objective scores. This paper gives the detailed experimental results, and verifies the effectiveness of the method. People watch the videos under different network environment and give the subjective score. Next the proposed method calculates the objective score. So the similarity between the subjective and objective score can be compared. At the same time, other objective methods are used to compare with this method. The experimental results show that this method can better improve the similarity between subjective and objective score.

Keywords: analytic hierarchy process, correlation coefficient, principal component analysis, quality of experience, video quality assessment

1 Introduction

With the rapid development of mobile internet technology, the service of network video is widely deployed. People can watch network video through different terminals, such as mobile phone, personal computer. It is predicted that network video service will be 80 percent of all network service in 2019. So the service providers focus on the video quality before people watch video. In this trend, the QoE has recently gained greater attention from academic research [1-2]. However, the video quality will be impaired by many factors, such as network environment, video content and terminal performance. It is difficult to measure the QoE.

* Corresponding Author

Many methods are designed to assess the video quality. As shown in Fig. 1, they are divided into subjective and objective method [3]. Subjective methods need people to watch the video and give the quality. It is a reliable method, but wasting time. The double stimulus continuous quality scale (DSCQS) and double stimulus impairment scale (DSIS) are commonly used to measure the video quality. ITU-T has provided the detail of them [4-5]. They are also crucial for evaluating the performance of objective methods. Because subjective methods have many disadvantages, the objective methods are developed.

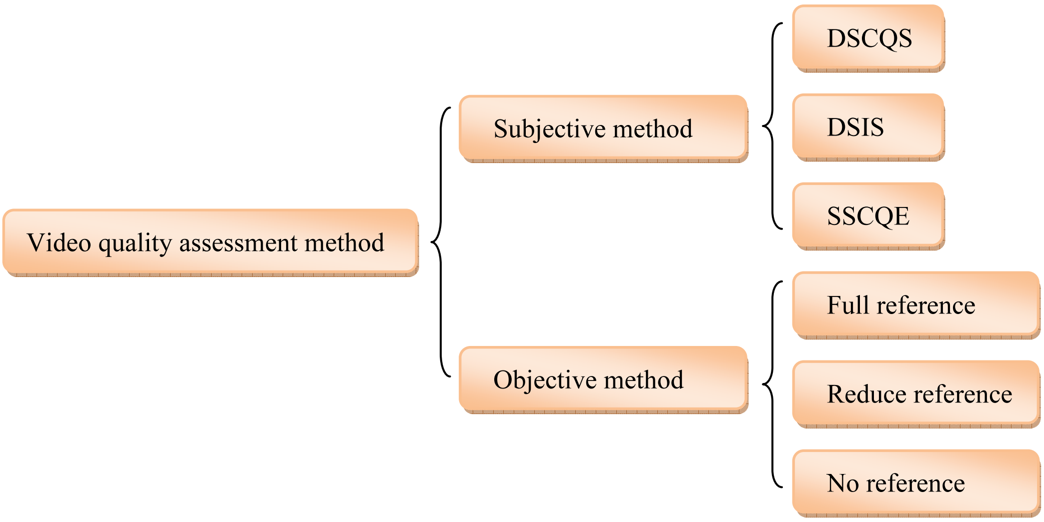


Fig. 1. The video quality assessment method

Objective methods have three kinds. They are full reference, reduce reference and no reference. Mean square error (MSE) and peak signal to noise ratio (PSNR) are the typical full reference method. Though the calculation of them is simple, they ignore the human visual perception [6-7]. Hu Sudeng has modified MSE and designed a low pass filter to preserve the perceptible spatiotemporal features [8]. Multi precision structural similarity index (MS-SSIM) has been proposed by Wang [9]. It compares the reference video and the distorted video to obtain the video quality. In addition, there are visual information fidelity (VIF), visual signal to noise ratio (VSNR), noise quality measure (NQM) and other methods. These methods commonly need reference videos. When the reference video is not available, the no reference method is needed. Markus Fiedler has proposed an exponential assessment model based on packet loss rate [10-12]. Maria Torres Vega uses deep neural network to model the video quality method [13]. Wei Zhang studies the saliency in objective video quality assessment [14].

However, there are many problems in QoE research. Some methods consider the network environment or the video content, but no method considers all the factors [15-17]. Some methods have fixed mathematical models. Their applicability is not universal. In this paper a comprehensive objective method based on AHP is proposed to assess the network video. The detail of this method is shown in Fig. 2. It considers QoC, QoT and QoS as impair factor. QoC reflects the features of the video, such as blur degree, blocking artifacts. QoT mainly reflects the performance of the terminal, such as CPU, resolution. QoS reflects the network performance, such as bandwidth, packet loss rate. Firstly all the impair factors are extracted. Next the CC between the impair factors and MOS is calculated. In this way, it can be seen that which factors are more related to the video quality. Because there are many impair factors, the PCA is used to reduce the dimensionality of factors. Secondly the AHP is used to give the weight of main impair factors. Lastly the method is constituted of different impair factors. This paper gives the detailed experimental results, and verifies the effectiveness of the method. Network videos are measured under different environment, and the impair factors are extracted. Meanwhile observers are organized to watch the network videos and given the subjective score. According to these experimental data, the objective method is built based on AHP. Finally, the proposed method is compared with other methods.

Table 1. The innovation of proposed method

Method	Point_1	Point_2	Point_3
Proposed method	Comprehensive	Optimized factors	Flexible
Other methods	Little	Original factors	Fixed

Table 1 shows the advantages and contributions of this method: 1. Many factors are comprehensively considered in a method, such as video parameters, network parameters and performance of terminal. 2. The extraction of parameter has been optimized by CC and PCA to reduce the dimension. 3. The use of AHP is an innovation in this domain. It can effectively establish the mapping relationship between the impair factor and QoE, and get accurate objective result. The proposed method can improve the similarity between the subjective and objective assessment.

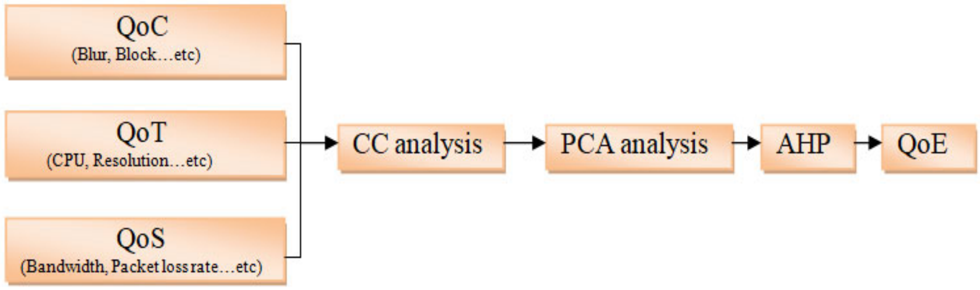


Fig. 2. The proposed objective method

The key research problems of this work are: 1.The input impair factors are optimized and considered in an objective assessment model. 2. The AHP is used to give the weight of every factor. It is a flexible method. The remainder of the paper is organized as follows: Section II introduces the different factors which impair the network video quality. In section III, the experimental system, videos is presented. The principle of algorithm and objective assessment method is presented in section IV. In section V, the experimental results are given to verify the proposed method. This paper is concluded in section VI.

2 The Impair Factors

As shown in Fig. 3, QoE is impaired by QoT, QoS and QoC. Video may be watched by various smart terminals, such as laptop, mobile phone and personal computer (PC). But the performance of terminal may impair the video quality. QoT is used to represent the terminal quality. QoS represents the network environment. People may watch video under different network environment. QoC represents the performance of video content. Table 2 lists the main impair factors. These factors are considered into the objective assessment model.

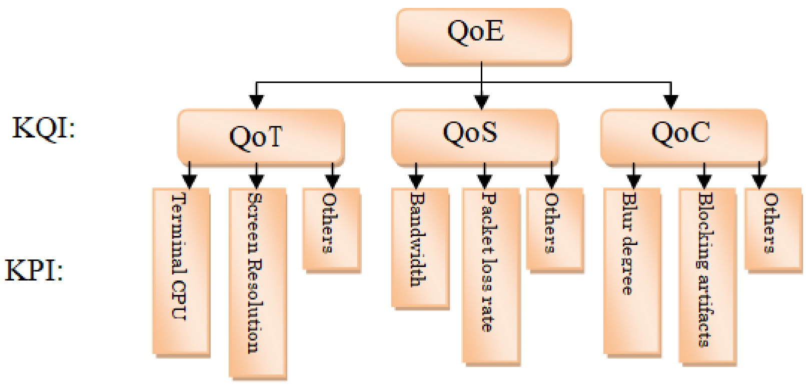


Fig. 3. The impair factors

Table 2. The main factors

KQI	KPI
QoT	Terminal CPU performance Memory consumption Screen resolution Operation system performance
QoS	Packet loss rate Bandwidth Delay Interuption rate Jitter
QoC	Blur degree Motion vector Blocking artifacts Contrast Ringing Noise Gradient activity

QoE can be expressed by equation (1). The key quality indicators (KQI_i, i = 1, 2, 3) are used to represent the QoT, QoS and QoC. α, β and γ are the weights.

$$QoE = \alpha KQI_1 + \beta KQI_2 + \gamma KQI_3 . \quad \textbf{(1)}$$

Key parameter indicators (KPI) is used to represent the impair factors which can be directly measured or calculated. The value of KQI is obtained by the KPI. So the KQI_i can be expressed by equation (2),

$$KQI_i = w_1 KPI_1 + w_2 KPI_2 + \cdots + w_n KPI_n . \quad \textbf{(2)}$$

w_1, $w_2 \ldots w_n$ are the weights. In the experiment, the weights of KPI_i are needed to adjust. The KPI_i is used to model the objective assessment method.

3 The Experimental Environment

In order to prove the validity of assessment method, the experimental system is built in Fig. 4. The video server is installed with Ubuntu 16.10 and Apache 2.4.2 to store video clips for observer. The network can simulate different bandwidth, packet loss rate and delay time. The observer can watch videos through Table, PC or mobile phone.

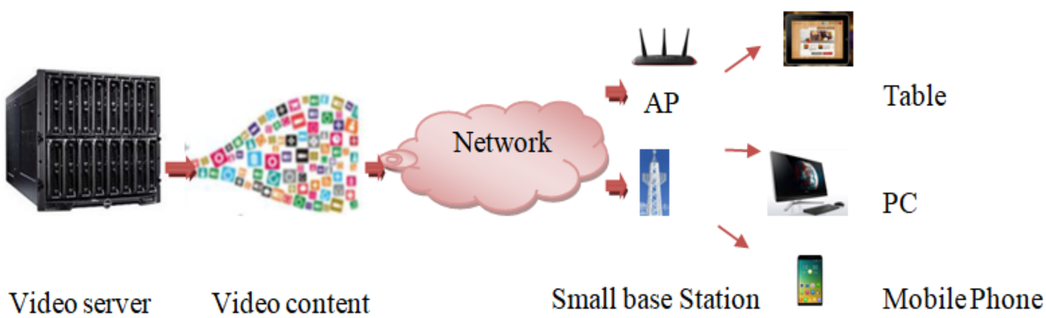


Fig. 4. The experimental system

Four videos are measured with different environment. The video is shown in Fig. 5, and the related information is recorded in Table 3. The Simpson is tested as an example. Table 4 lists the network environment emulated by the experiment system. The bandwidth is selected from 8Mbps to 4Mbps, emulating the bandwidth of common home users. The delay time is changed from 50ms to 200ms. The packet loss rate is varied from 0.1% to 1% to investigate the impact of packet loss rate.

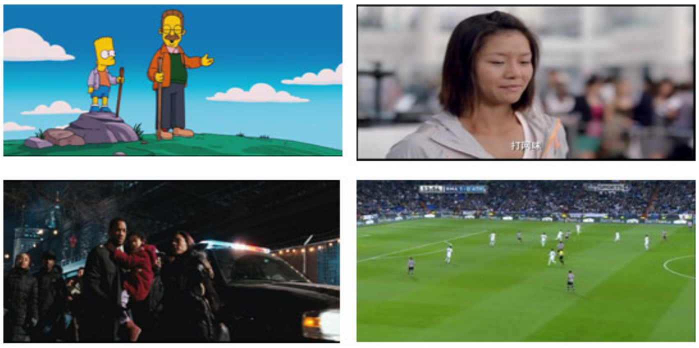


Fig. 5. The videos

Table 3. The information of videos

Num	Resolution	Bit rate (Mbps)	Video	Time (s)
1	1280*544	4.28	Simpsons	200
2	640*480	5.16	Advertisement	30
3	1920*816	8.23	Movie clip	123
4	640*480	10.85	Sport	254

Table 4. The experimental index

Bandwidth (Mbps)	Packet loss rate (%)	Delay time (ms)
8, 6, 4	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1	500, 100, 150, 200

Meanwhile 23 people take part in the experiment and give the subjective assessment scores. The score is given from 1 to 5. All the scores for the same video are averaged. At last the average result is given to determine the MOS. Fig. 6 shows the MOS under different network environment. When the network environment deteriorates, the MOS decreases.

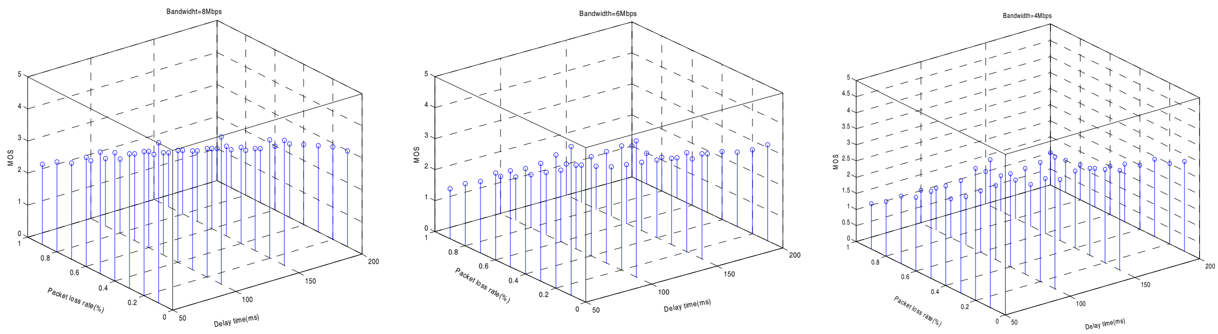


Fig. 6. The MOS under different network environment

According to Table 2, every *KPI* can be measured. These factors make up a matrix of 40 rows and 16 columns under different bandwidth. The rows represent the number of test. The columns represent the number of factors. These factors will be used to model the objective assessment method.

4 The Proposed Method

The proposed method has four steps. The programs are as follows:

```
--------------------------------------------------------------------------------
Program begin (input parameters, Output QoE)
{var input parameters;
   preprocess (parameters);%Firstly all input parameters should be preprocessed
   CC(parameters); %Secondly the correlation coefficient between the
   parameters and subjective MOS is calculated.
```

```
   PCA(parameters);%Thirdly the dimension of parameters are reduced.
   AHP(parameters, ω1, ω2,... ωN);%Lastly the AHP is used to give the weight of
   factors to model the objective method.
 }
return QoE
end.
```

Next, the detail of this method is presented.

4.1 The Preprocessing

The measured *KPI* should be changed into dimensionless parameter. The conversion mechanism is equation (3),

$$Q_{final} = Q_{right} + (Q_{left} - Q_{right}) \times \frac{|P_{test} - P_{right}|}{P_{right} - P_{left}}. \quad \textbf{(3)}$$

Q_{final} represents the dimensionless value, Q_{right} and Q_{left} represents the region of dimensionless value. P_{test} represents the measured value. P_{right} and P_{left} represent the region of measured value. According to the Simpson's experiment, Table 5 gives the measured and dimensionless value of partial network parameters. If the measured delay is 80ms, Q_{final} = 3 + (4-3) × |80-100|/(100-50) = 3.4. If the measured packet loss rate is 0.2%, Q_{final} = 4+(5-4)×|0.2-0.2|/(0.2-0.1) = 4.

Table 5. The impair factor of QoE

Dimensionless value	5-4	4-3	3-2	2-1
Delay time (ms)	10-50	50-100	100-150	150-200
Packet loss rate (%)	0.1-0.2	0.3-0.5	0.6-0.8	0.9-1

In the same way, other *KPI* can be set and changed into dimensionless value. All the dimensionless value of factors will be 1to 5.The MOS is also 1to 5. So it is easy to compare with the MOS.

4.2 The Correlation Coefficient

Correlation coefficient is proposed by Karl Pearson [18-19]. The equation (4) is used to compute the correlation between impair factors and subjective MOS. *Cov(X, Y)* is the covariance of *X* and *Y*. *Var* represents the variance of factor.

$$\rho_{XY} = \frac{Cov(X,Y)}{\sqrt{Var[X]Var[Y]}} \ , \ |\rho_{XY}| \le 1 . \quad \textbf{(4)}$$

In this way, the CC of every *KPI* can be got. The value of $|\rho_{XY}|$ is bigger, the correlation between *KPI* and MOS is bigger. For example, if the CC of packet loss rate is 0.8, the CC of delay time is 0.6. It represents that the correlation between subjective MOS and packet loss rate is bigger. According to the CC of every *KPI*, it is possible to find out which factors are more important.

4.3 The PCA

Through the above analysis, it can be seen that some factors are more important than other factors. On the other hand, there are many impair factors of video quality. So the PCA is used to reduce the dimension of *KPI*.

$$B = \begin{bmatrix} a_1 & b_1 & . & . & p_1 \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ a_{40} & b_{40} & . & . & p_{40} \end{bmatrix}_{40\times 16} . \quad \textbf{(5)}$$

Firstly, the mean matrix B is constituted of different factors. Next the average values of every row can be got,

$$average\ row = \frac{a_i + ... + p_i}{N} . \quad \textbf{(6)}$$

Secondly, every row minus the corresponding average value to get matrix A. The equation (7) gives the covariance matrix C. λ_i is the characteristic value of C. α is the contribution rate. In the experiment, α is chosen 80% and 90%. U is the corresponding eigenvector. Q is the matrix after dimensionality reduction. Lastly, the Q is used to model the objective MOS.

$$C = \frac{A \cdot A^T}{16} , \quad \textbf{(7)}$$

$$\alpha = \frac{\sum_{i=1}^{d} \lambda_i}{\sum_{i=1}^{N} \lambda_i} , \quad \textbf{(8)}$$

$$U = [u_1, u_2, ... u_d] ,\ Q = U^T A . \quad \textbf{(9)}$$

4.4 The AHP

In this paper, AHP is used to give the weight of impair factors after dimensionality reduction [20]. It solves complicated tasks by decomposing them into a hierarchy of simpler sub-portions. The sub-portions are usually called decision factors and weighted according to relative importance [21-22].

At first the different factors must be compared with each other, and be distributed weight. An example of the AHP matrices is shown in Table 6. The comparison scale uses a range of 1 to 9. 1: Equally important, 3: Moderately more important, 5: Strongly more important, 7: Very strongly more important, 9: Extremely more important. The elements of the AHP matrices can equal 1, 3, 5, 7, 9, 1/3, 1/5, 1/7, or 1/9.

Table 6. The judgment scale AHP

1	The two factors are the same impotant
3	One factor is a little important than the other
5	One factor is obviously important than the other
7	One factor is more important than the other
9	One factor is greatly important than the other
2, 4, 6, 8	Between two adjoin important

According to Table 6, matrix A is constructed. It has three characteristics: $a_{ij} > 0$, $a_{ij} = 1/a_{ji}$, $a_{ii} = 1$,

$$A=\begin{bmatrix} 1 & a_{12} & . & . & a_{1n} \\ a_{21} & 1 & . & . & a_{2n} \\ a_{31} & a_{32} & 1 & . & a_{3n} \\ . & . & . & . & . \\ a_{n1} & a_{n2} & . & . & 1 \end{bmatrix}. \tag{10}$$

In order to guarantee single hierarchical arrangement, the algorithm gives equation (11),

$$Aw=\lambda_{max}w. \tag{11}$$

w is the normalized eigenvector. The components of *w* are decision factors weight. *w* is computed by the following steps:

$$b_{ij}=\frac{a_{ij}}{\sum_{i=1}^{n}a_{ij}}, \tag{12}$$

$$w_i=\frac{1}{n}\sum_{j=1}^{n}b_{ij},(i=1,2,...n), \tag{13}$$

$$w_i=(w_1,w_2,...w_n)^T. \tag{14}$$

So the weight w_i can be get. Then the consistency must be examined:

$$\lambda_{max}=\frac{1}{n}\sum_{i}\frac{(Aw)_i}{w_i}, \tag{15}$$

$$CI=\frac{\lambda_{\max}-n}{n-1}, \tag{16}$$

$$CR=\frac{CI}{RI}. \tag{17}$$

RI is random number which can be chosen in Table 7. If $CR < 0.1$, the matrix *A* is reasonable.

Table 7. The data range of RI

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

But the matrix *A* needs order consistency. Because $a_{ij}>1, a_{jk}>1,\ a_{ki}>1$, the weight will be appeared *I* > *j* > *k* > *i*. This condition is unreasonable. The matrix *A* must be checked the order consistency. At last every weight must be normalized, and computed by equation (18),

$$w_i=\sqrt[n]{W}_i/\sum_{i=1}^{n}\sqrt[n]{W_i}. \tag{18}$$

After all the steps, every factor has its own weight. The objective model has characteristic factors with different weight.

5 Experimental Results and Analysis

The proposed objective method is strictly in accordance with the above theory. Firstly four videos are tested under different experimental environment. The subjective MOS is given to check the accuracy of objective method. Secondly the impair factors are extracted. All factors are processed by the four steps. These *KPIs* have been optimized by PCA. Lastly the objective MOS is constituted by different factors with weight,

$$objective\ score = w_1 KPI_1 + \ldots + w_n KPI_N . \qquad \textbf{(19)}$$

All the above steps are completed in Matlab R2011b on a PC with CPU I3-4130 at 3.4 GHz CPU, with 4 GB of RAM running 64 bit Microsoft Windows 10. The resolution of PC is 1680×1050. Meanwhile, the PSNR, weighted signal to noise ratio (WSNR), structural similarity index (SSIM), MSSIM methods are used to compare with the proposed method. The Spearman and Pearson coefficients are used to analyze the similarity between the subjective and objective scores. If the value of these coefficients is bigger, the similarity is bigger.

$$Spearman = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{S_i - \overline{S}}{D_i}\right)\left(\frac{S_{pi} - \overline{S_P}}{D_{pi}}\right), \qquad \textbf{(20)}$$

$$Pearson = \frac{\sum (S_i - \overline{S})(S_{pi} - \overline{S_p})}{\sqrt{\sum (S_i - \overline{S})^2 \sum (S_{pi} - \overline{S_P})^2}} . \qquad \textbf{(21)}$$

As shown in Table 8 and Table 9, the coefficients of the proposed are above 0.9. It is better than other methods. It proves the proposed method can improve the accuracy of objective score. The objective scores of this method are close to the subjective scores.

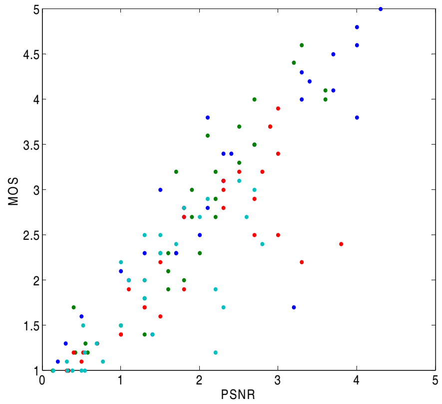
Table 8. The Spearman of every method

Algorithm	Simpsons	Advertisement	Movie clip	Sport	Average
PSNR	0.63	0.59	0.61	0.58	0.60
WSNR	0.52	0.48	0.54	0.51	0.51
SSIM	0.72	0.63	0.69	0.72	0.69
MSSIM	0.79	0.82	0.75	0.84	0.80
The proposed method (contribution rate α =80%)	0.87	0.88	0.86	0.87	0.87
The proposed method (contribution rate α =90%)	0.92	0.90	0.91	0.90	0.91

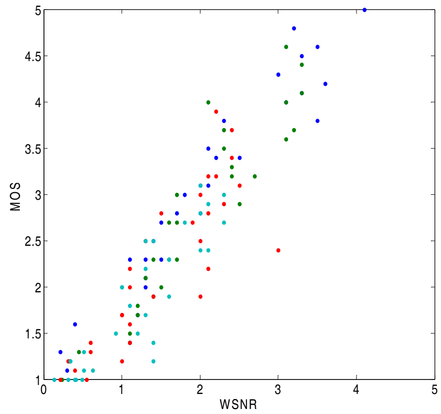
Table 9. The Pearson of every method

Algorithm	Simpsons	Advertisement	Movie clip	Sport	Average
PSNR	0.64	0.60	0.61	0.58	0.61
WSNR	0.52	0.49	0.54	0.51	0.52
SSIM	0.72	0.64	0.69	0.73	0.70
MSSIM	0.80	0.82	0.75	0.83	0.80
The proposed method (contribution rate α =80%)	0.88	0.89	0.85	0.88	0.88
The proposed method (contribution rate α =90%)	0.93	0.91	0.91	0.92	0.92

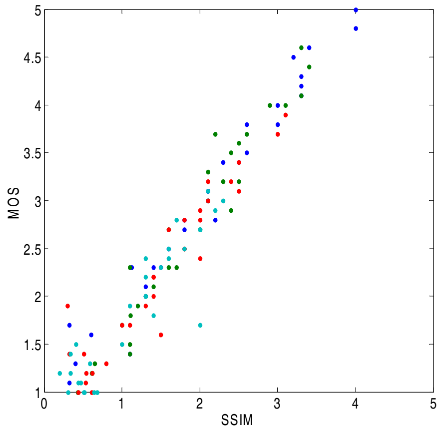
Every video has been tested 120 times, so there will be 120 subjective and objective scores. Fig. 7 shows the subjective and objective scores of Simpson. The subjective and objective scores of proposed method have a good linear relationship. It improves the similarity between subjective and objective score. Other methods are sparse. On the other hand, it can be seen that the value of contribution rate α is bigger; the more characteristic factors are obtained. So the objective scores are improved more.



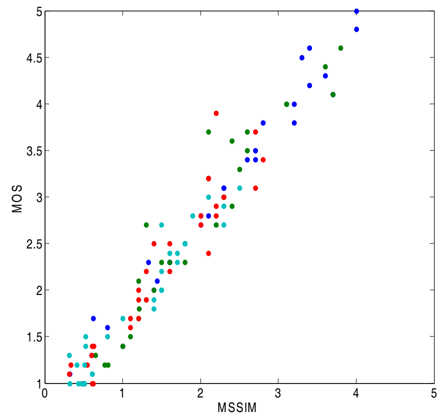
(a) PSNR and MOS



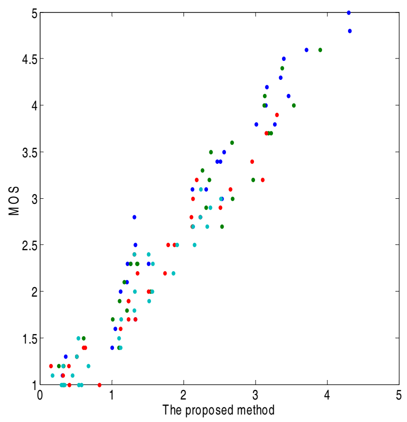
(b) WSNR and MOS



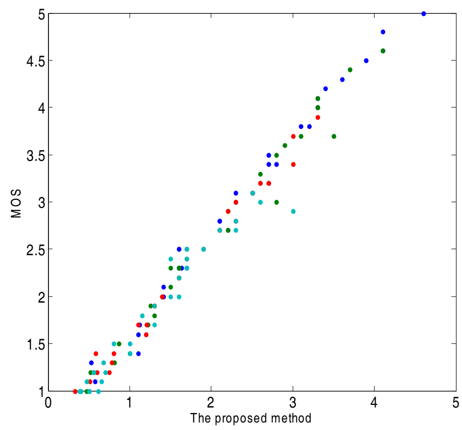
(c) SSIM and MOS



(d) MSSIM and MOS

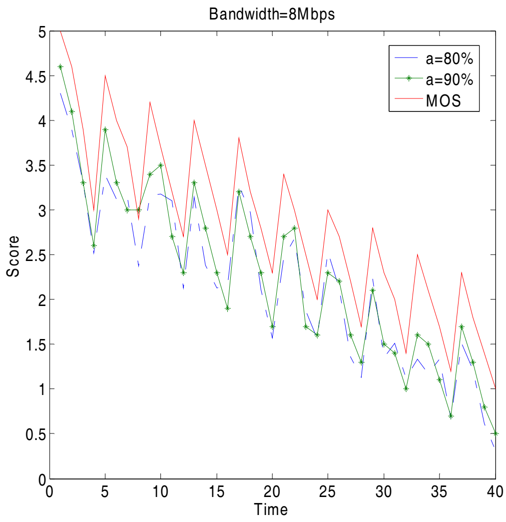


(e) The proposed method and MOS (α =80%)

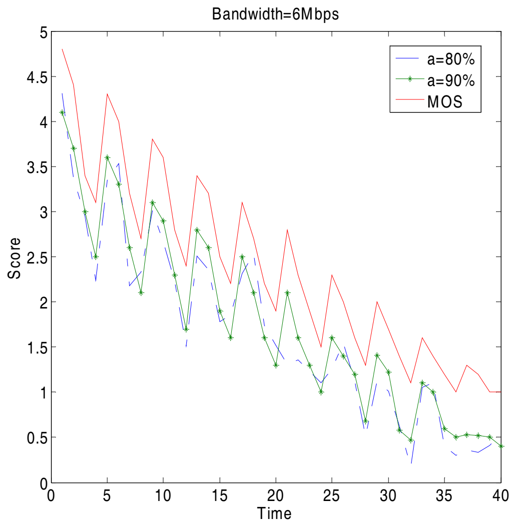


(f) The proposed method and MOS (α =90%)

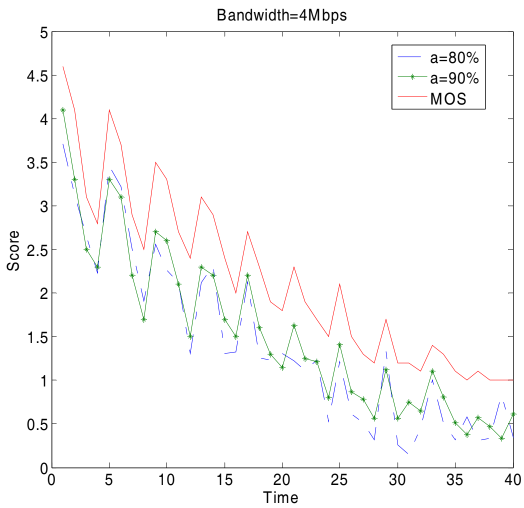
Fig. 7. The similarity between the subjective and objective MOS



(a) The scores under 8Mbps



(b) The scores under 6Mbps



(c) The scores under 4Mbps

Fig. 8. The scores under different bandwidth

Fig. 8 shows the scores of Simpson under different bandwidth. It can be seen that the scores of proposed method (α = 80% or 90%) are close to the subjective scores. This method effectively improves the objective method. It comprehensively considers many impair factors. At the same time, it can adjust the weight, according to the importance of impair factors. The method has good applicability.

6 Conclusion and Future Work

In this paper, an objective assessment method based on AHP is proposed. The main factors which impair the video quality are considered, such as QoT, QoS and QoC. Firstly the measured factors are changed into dimensionless value. Secondly they are analyzed by CC and PCA. Thirdly the AHP is used to measure the weight of main impair factors. Lastly the objective method is composed of different factors. In order to prove the validity of proposed method, four videos are tested under different experimental environment. Meanwhile other methods are compared with it. The results show that this method can improve the similarity between the objective and subjective score.

This method has many advantages: 1.Many factors are comprehensively considered in a model, including video parameters, network parameters and performance of terminal. 2. The CC and PCA are used to optimize these parameters. 3. AHP is used to establish the relationship between the impair factor and QoE, and get accurate objective result.

The next steps more impair factors will be consider and improved the objective QoE model. The accuracy of this method will be improved.

Acknowledgments

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