Adaptive compression method of underwater image based on perceived quality estimation

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***Abstract*—** Underwater image compression is one of the most important and essential part in underwater image transmission system, the effective image quality assessment and estimation of the compressed image can make the system adjust the compression ratio better in the compression process, improve the efficiency of image transmission system. This paper respectively estimate the underwater image compression perceived quality based on the strategy of coding compression and the compression strategy of compressive sensing, built model base on the mapping between image activity measurement(IAM) and BPP-SSIM curve, and obtain model parameters, then predict the perceived quality of image compression based on image activity measurement, compression ratio and compression strategy. The experimental results show that the model can effectively fit the quality curve of underwater image compression, according to the rules of the parameters in this model, the perceived quality of underwater compressed image can be estimated in the small error range. The presented method can effectively estimate the perceived quality of underwater compressed image , and effectively balance the relationship between the compression ratio and compression quality, reduce the pressure of the data cache, and improve the efficiency of underwater image communication system.

***Keywords*—**underwater image compression, coding compression, compressive sensing, compression quality estimation.

I. INTRODUCTION

AS the eyes of underwater autonomous equipment, images have the visual effect that voices and texts are difficult to express, which is increasingly becoming the main business form of underwater wireless communication, so underwater images have broad and pressing demand in the marine exploration, national security, and many other applications. But the main difficulty in the current underwater image application is the contradiction between the large data volume of underwater image (1.2M--15M) and the acoustic communication bandwidth (3-5Khz).

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Under the condition of limited channel bandwidth and certain communication transmission rate, in order to improve the efficiency of image communication, image data need to be compressed as far as possible; on the other hand, in order to improve the quality of the reconstructed image, transmitter need to reserve the image data as much as possible. An important part of the image compression is to make an effective trade-off between the compression ratio and compression quality. In recent years, on raising the compression ratio and improving reliability, reference[1] analyzes the impact of parameters of filter group on the compressed image, which determines the selection of the filter in the process of encoding; reference [2] establishes a linear regression estimation model of different filter and compression quality, using predictive model to assess the compression effect of filter before images coding; reference[3] studies the relationship between different ROI size and the compressed image quality and build quality estimation model, predict the compression image quality from ROI and choose proper compression algorithm; reference[4] uses image quality estimation model for image classification, and improve performance through setting different compression parameters for different types image.

However, the above documents most studies only consider compression part, lack of comprehensive research combined image characteristics and channel condition. In underwater communication, also need to consider the use of storage space and bandwidth allocation, to consider the complexity of the algorithm and occupied cache. Therefore, this paper presents a compressed image quality fast estimation model based on perception mapping and underwater image adaptive compression method, firstly use image activity measurement (IAM) to distinguish the different image characteristics, and on the basis of summing up the rules of different image compression, use the perceived service quality vector decomposed the complex IAM-BPP-SSIM relationships into several two-dimensional relationships, through the analysis and and fitting relationships, obtain the estimation formula that use image IAM value to estimate the image compression quality quickly. Using the estimation formula can guarantee that the quality of compressed images meet the needs of human eyes, on the other hand, storage space can better use and bandwidth source can be better allocated.

Sections of this paper is as follows, the first part introduces the principle of acoustic image compression system; in the second part, two kinds of underwater image compression method is applied to the underwater image compression respectively, then summarizes the rules of underwater image compression; The third part establishes compression quality estimation mode according to the rules of the compression; The fourth part verifies the effectiveness of the model by experiments; and the last part is the conclusion.

II. Underwater Image Features and Compression Method

In order to improve the compression rate, to adapt the communication needs of the limited energy of underwater node and limited bandwidth, compression strategy of underwater acoustic image is to allow certain compression distortion in the case of not affect visual perception. How to accurately set the compression ratio in accordance with the visual perception is the difficulty point of underwater acoustic image communication. Compression rate setting is not only related to the encoder, also related to the communication link, it needs to take the features of link into consideration, and then obtain the reference compression ratio. The traditional approach is by sparse transformation, the energy concentrated in a few coefficients, and set the coefficients below one certain threshold in order to realize the compression. The peak signal-to-noise ratio (PSNR) method is mainly used to measure the effect before and after compression, but there is a deviation between the PSNR and human visual perception, so the traditional methods can only rely on experiences to set threshold, cannot adjust optimally according to actual situation. Therefore, it is difficult to accurately find the inflection point by using energy method. In the compression of underwater image, apart from focusing on the performance affect of codec, also need to consider the coding error effect of the channel bit error rate, the bad condition of underwater acoustic channel brings big challenge to quality control, underwater images have large amount of data, usually need to be compressed and coding in order to meet the extremely limited bandwidth. And because of the time-varying of multipath underwater acoustic channel, a single compression scheme is very difficult to adapt to fast changing channel conditions.

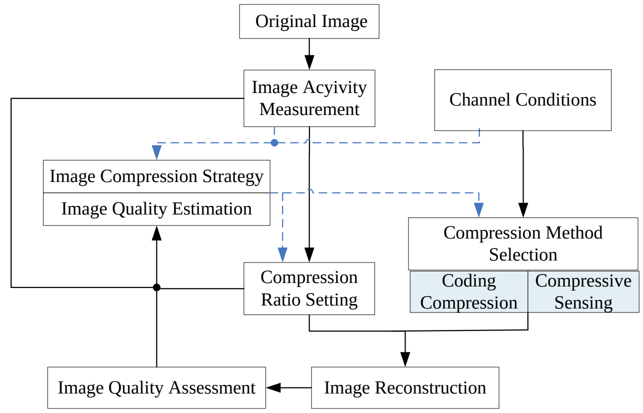


Fig. 1 The mechanism of underwater image adaptive compression process

This paper establishes different compression encoding schemes for different channel characteristics, and uses perceived quality as the optimization goal of image compression, proposes an adaptive compression mechanism of underwater image in different channel conditions, the principle block diagram is shown as figure 1. Firstly, different compression ratios are set for images with different IAM under different compression methods. The image quality of the reconstructed image is evaluated and the rules of compression image quality is summarized. Subsequently, the perception quality of different images under different compression methods is modeled, and the image activity is mapped to the compression rate and the compression quality, then the fast estimation system is generated. Finally, image compression coding strategy is obtained according to the IAM and channel conditions, make the compressed image code stream is suitable for transmission channel, and the image reconstruction quality conforms to the requirements of visual perception.

A. Image Compression Strategy Based on Encoding Compression

With the expanding of application of image, the more requirements for image coding, image coding need to have a high compression ratio and better reconstructed image quality, making the image compression effect better satisfy the human eye vision. Embedded wavelet coding makes full use of the space of wavelet transform compression property and the distribution similarity of transform coefficient, the encoding efficiency of the wavelet transform is much higher than that of JPEG based on DCT transform. And many improved algorithm based on Embedded Zerotree wavelet Coding also arises at the historic moment, such as SPIHT(Set Partitioning In Hierarchical Trees) algorithm, SPECK(Set Partitioned Embedded bloCK coder) algorithm, LZC(Listless Zerotree Coding) algorithm, etc.

The SPIHT[5] compression coding algorithm is the representative progressive code flow compression coding algorithm based on the zero-tree coding EZW algorithm, its spatial orientation tree structure definition is shown in Figure 2. SPIHT algorithm generates an embedded bit stream, if appear arbitrary interrupt point in the process of data stream transmission, it can extract and reconstruction image according to the code that has received, has the good progressive transmission characteristics.

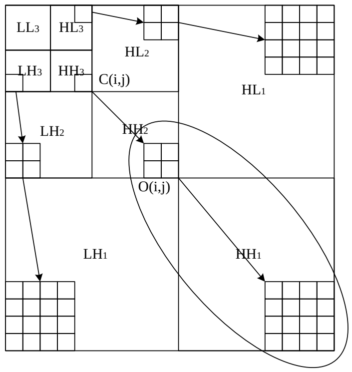


Fig. 2 SPIHT spatial orientation tree structure

SPIHT compression algorithm is based on image wavelet coefficients and the human visual characteristics, the quality of reconstructed image under the condition of low compression ratio is good, and SPIHT algorithm has simple structure, low complexity. SPIHT encode the important information of image with higher priority, information data contribute lager for image reconstruction set in front of the bit stream, however, these important bits are more relatively sensitive to error , often one bit error could make the reconstruction images hard to recognize. Data bits of different positions have different importance, when an important bits appear error, image reconstruction quality will have great impact, reconstructed image will appear color piece accumulation, pixels arranged, unable to get image information of the original image. Therefore, the robustness of SPIHT code flow is low, and the important bit in the code flow needs to be protected when communicating and transmitting.

B. Image Compression Strategy Based on Compressive Sensing

In 2006, Compressive Sensing (CS) theory was propose [6-7]. The Compressive Sensing theory mainly consisted of sparse representation of signal, random coding measurement and signal reconstruction. It combines the sampling and compression of the signal, breaks the limit of shannon sampling theorem, and completes the compression when the signal is sampled at a low rate. For a discrete real value signal x of length N, t it can be expressed in a set of basis linear:

$$x = \Psi a \quad (1)$$

When the projection of signal x on a basis Ψ has only $K(K << N)$ non-zero coefficients, x can be regarded as a sparse signal on the basis Ψ. Encoding measuring model of compressive sensing theory is not directly measured signal x, but project to a set of low dimensional measurement vector Φ by uncorrelated measurement , and the measured values are obtained:

$$y = \Phi x \quad (2)$$

Because the number of the measured value y is far less than the number of the sparse coefficients a, the compression sampling of the signal is realized. When the convergence of the algorithm is guaranteed, the reconstruction signal can be realized by solving the optimization problem of the norm.

The compressive sensing has good anti-noise performance, because the reconstruction algorithm can obtain the important K sparsity component and suppress the other noise components to zero. Because RIP rules limit, all of the measured values for reconstruction algorithm have the same importance, in other words , there is no difference of measured values of image, so the compressive sensing in communication and channel coding has good robustness.

Reference[8] samples and measures the image block according to the bispectrum and Image Activity Measurement, image blocks with different saliency are assigned different sampling rates, the experiments show that this method has better image compression quality and higher robustness. Based on above method, the frame process of adaptive compression of underwater images is as follows:

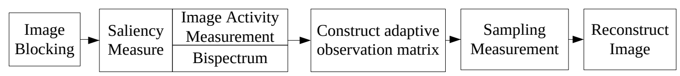


Fig.3 Adaptive compression sensing flowchart

III. MAPPING BETWEEN IMAGE ACTIVITY MEASUREMENT AND COMPRESSION QUALITY

A. Image Activity Measurement

Images with different texture complexity also have different degree redundancy, and the quality of reconstructed images in the same compression ratio can be different. Images with simple edge texture structure have less information and lager degree of redundancy, therefore reconstruction quality in lower compression ratio will be better than the images with complex texture structure, on the contrary, images with complex structure and more texture edges have large amount of information, low redundancy, at the same compression rate after compression, the image information lost will be more, image quality will be inferior to the image with simple structure. Therefore, on the premise that the perception quality of compressed image is not affected , image compression needs to set different optimal compression ratios for the images with different texture complexity.

Reference[9] put forward that Image Activity Measurement (IAM) can be regarded as indicator of the complexity of the Image, under the same compression ratio, the higher IAM value, the poor image compression quality, on the contrary, the lower IAM value, the better compression quality of image.

The image region with edge and the texture is defined as the image active area, the more complex the active areas, the higher IAM of image. The saliency of the image is set based on the IAM:

$$IAM_0 = \frac{1}{M*N}\left[\sum_{i=1}^{M-1}\sum_{j=1}^{N}\sqrt{I(i,j)-I(i+1,j)} + \sum_{i=1}^{M}\sum_{j=1}^{N-1}\sqrt{I(i,j)-I(i,j+1)}\right] \quad (3)$$

Where M,N is the size of the image. The larger the value of IAM indicates that the image structure is more complex, and the edge texture is more. The smaller value indicates that the image structure is simple and the edge texture is less.

B. Compression Image Quality Assessment

After the image is compressed, accompanied by the loss of image information, distorted degree of compressed image is different under the different compression ratios, sensitivity of the human visual system is different to the different structures and different frequencies of image, visual perception quality is not proportional to the bit error rate, can not depend on the single bit error rate or the amount of information data to measure the image quality. Therefore, it is necessary to chose one image quality evaluation index to effectively measure the quality of compressed image, and effectively evaluate image compression quality according to human visual characteristics.

Different quality evaluation algorithms have different sensitivity and accuracy for different types of images. The main distorted features of image compression are the fuzzy and block effects caused by the quantization, and need to select the most effective evaluation algorithm for the compressed image. The full reference image quality assessment (FRIQA) algorithm use all the information of the original image to compare with the distorted image, and then the comprehensive perception error can be evaluated and the result is relatively reliable. Therefore, 8 FRIQA algorithms are compared in this paper. The imaging principle of natural optical image is similar to underwater optimal image, the main distorted features of natural compressed image are also fuzzy or block effect, so choose the compressed image in 4 natural image databases as sample to evaluate the FRIQA performance, set SROCC, KROCC, PLCC, RMSE as performance indexes, evaluate the consistency of the algorithms' quality perception values and subjective evaluation scores, the image database and performance are shown in table 1, table 2.

Table 1 Natural image database

Image Database	The number of reference images	Compression type	The number of distorted images
LIVE[10]	28	JPEG	233
		JP2K	227
TID2013 [11]	25	JPEG	125
		JP2K	125
CSIQ [12]	30	JPEG	150

Table 2 Performance of image quality assessment algorithms in the natural image database

type	Index	FSIM [13]	GMSD [14]	GSM [15]	IW-SSIM [16]	PSNR	SSIM [17]	UIQ [18]	VIF [19]
JPEG	SROCC	0.855	0.853	0.882	0.86	0.715	**0.904**	0.851	0.89
	KROCC	0.647	0.647	0.687	0.655	0.501	**0.719**	0.649	0.699
	PLCC	0.877	0.874	0.879	0.874	0.681	**0.897**	0.852	0.896
	RMSE	0.127	0.129	0.126	0.129	0.194	**0.117**	0.139	0.118
JP2K	SROCC	0.905	0.91	0.918	0.9	0.795	**0.933**	0.871	0.933
	KROCC	0.73	0.737	0.748	0.726	0.59	**0.771**	0.69	0.778
	PLCC	0.902	0.906	0.908	0.898	0.792	**0.921**	0.865	0.924
	RMSE	0.121	0.118	0.117	0.123	0.171	**0.109**	0.14	0.107

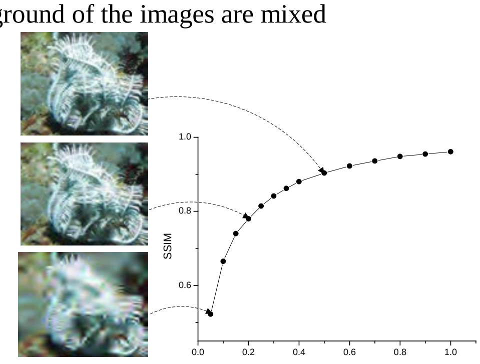
It can be seen from the above table that the SSIM quality assessment algorithm is optimal quality assessment for compressed image, so the SSIM can be used as the quality perception index of compressed image. SSIM combines the luminance, contrast and structure of the reference image and distorted image to obtain the quality evaluation score, corresponding to the main distorted features of the compressed image.SSIM is defined as follows:

$$SSIM(x,y)=\frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^{\ 2}+\mu_y^{\ 2}+C_1)(\sigma_x^{\ 2}+\sigma_y^{\ 2}+C_2)} \qquad (4)$$

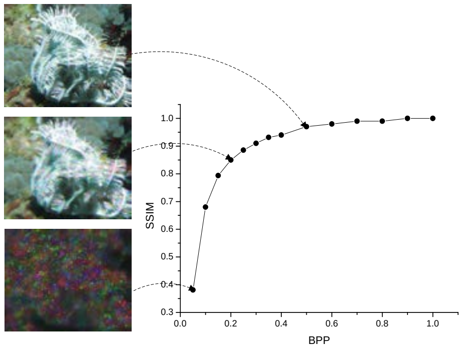
Where μ_x and μ_y are average brightness values of local pixel block of the original image and the distorted image, σ_x and σ_y are the standard deviation of brightness of local pixel in the two images, σ_{xy} is the correlation coefficient of brightness in two corresponding pixels of the two images , C is a small value.

SPIHT compression and adaptive CS compression of the underwater images are performed respectively, the compressed image and SSIM values of different compression rates are shown in figure 4.

Under different compression ratio, the image distortion degree also different, with the increase of the BPP, image quality also gradually increases, but the increase trend is nonlinear. because compression method is different, the curve shape of BPP-SSIM is also different, the SSIM values of images can better reflect the quality of image compression. The main distortion feature of SPIHT compression is fuzzy, which edge and texture broaden, the main distortion feature of adaptive CS compression is texture unclear, light color area will appear bright spot, under low compression ratio, the foreground and background of the images are mixed



(a)SPIHT compression



(b)Adaptive CS compression

Fig.4 Underwater image compression curve and effect

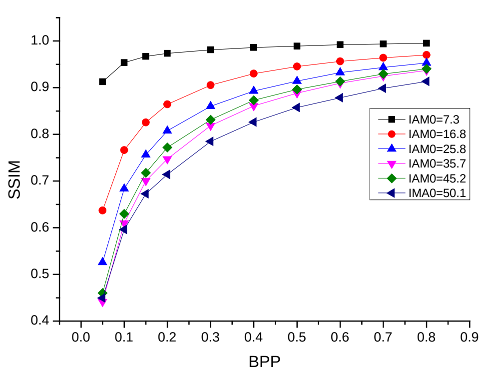
C. Mapping Between IAM and Perceived Quality

For different kinds of images with different IAM_0, the compression quality will be different in the same compression rate, and the corresponding compression quality curve will be different. To validate this compression phenomenon, 6 underwater images with different IAM_0 values are selected separately to perform SPIHT compression and adaptive CS compression, those image types contain single objective and multi-objective, close shot, long shot, and simple texture , complex texture image, as shown in figure 5. In the low compression ratio (BPP= 0.05~ 0.3), the compression step was set at 0.05, and the compression step is 0.1 at the higher compression ratio (BPP =0.3~ 0.9), so the range of the independent variable is 0.05~ 0.9. The SSIM value is set as the representation of image quality , the SSIM values of different images are calculated at different compression rates, and plot drawn-scatter graph of each image. The results are shown in figure 6.

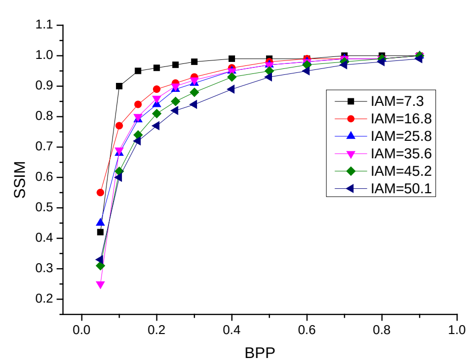
(a) IMG20 IAM_0=7.3 (b) IMG9 IAM_0= 16.8 (c) IMG19 IAM_0=25.8

(d) IMG6 IAM_0=35.7 (e)IMG7 IAM_0= 45.2 (f)IMG3 IAM_0=50.1

Fig.5 Underwater image

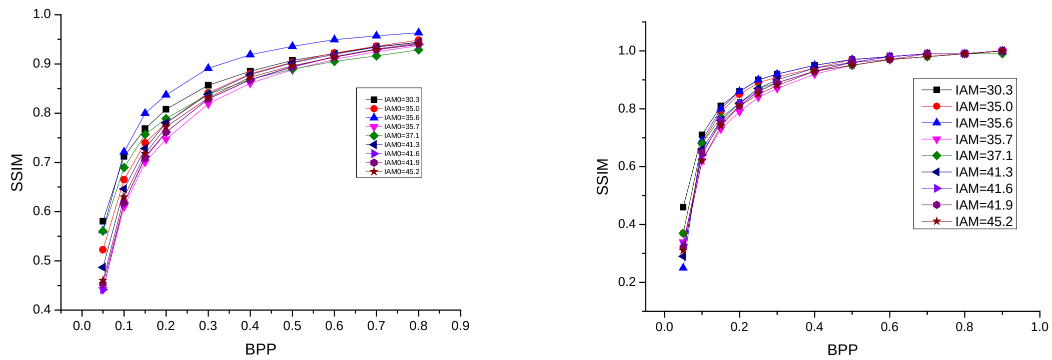


(a)SPIHT compression



(b)Adaptive CS compression

Fig.6 $BPP-SSIM$ curve of different image compression



(a)SPIHT compression (b)Adaptive CS compression

Fig.7 $BPP-SSIM$ curve of images with similar IAM_0

As shown in figure 6, the compression curves for different IAM_0 images are not exactly the same, but the trend of a set of curves follows the same basic shape. The slope and position of curve are the main differences, which associated with the IAM_0 value of image, the curve in the upper left corner position are corresponding to the images with low IAM_0 value and the image and tilt slope of curve is low, and curves in the lower right corner are corresponding to the images with big IAM_0 value and the slope of the curve is higher.

In fact, the curve located in the upper left corner means that low activity image can achieve higher compression quality compared with high activity image. when the compression rate of the image is lower than a certain threshold, the compression quality of the image drops sharply, and this threshold is also related to the image activity measurement. And the curve of the lower right area in the corner means that high activity image need higher compression ratio makes the image quality can reach satisfied quality, and the compression curve of high activity image reaches the optimum quality more stable.

According to IAM_0 of the image, each BPP-SSIM curve has its corresponding shape and slope, the IAM_0 and BPP-SSIM curve are mapped to each other. In order to verify this mapping relationship, 9 images with similar to IAM_0 value are selected as shown in appendix, and the compression curve of them is shown in figure.7, and images with similar IAM_0 values have similar compression curve in figure.7. Therefore, different quality curves can be distinguished by IAM_0, and infer the shape and trend of the curve according to IAM0, then obtain the compression quality curves of different images.

IV. Fast Quality Estimation Model of Underwater Image Compression

A. *Image quality estimation model based on perception mapping*

Known from Ⅲ.C that the quality of compressed image depends on the image compression ratio and IAM_0, and follow the rules: the first is that the each curvature degree of image compression quality curves are different, when the IAM_0 values of images have large difference, the curves have larger interval, when the IAM_0 values are similar, the interval between the curve is small, and each curve has its specific curve slope; Secondly, in different BPP ranges, increase rate of curve is also different, when BPP is less than a certain threshold, SSIM increase rapidly with the increase of BPP, but when BPP exceeds a certain threshold, SSIM only increases slowly or tend to stable; In addition, in the compression process, the maximum objective quality that images can achieve is different, that is, each image compression quality has its upper limit threshold.

According to the above image compression rules and parameters, the fitting method can be used to fit the BPP-SSIM curve. Perceived Quality of Service(PQoS) model is proposed in reference[20]: Perceived Quality can be described by a Quality Vector (QV), such as image compression quality vector can be represented as $QV=(q_1,q_2,\cdots,q_n)$, where $q_k(k=1,2,\cdots,n)$ is the influence parameters of the quality vector. So the image compression quality can be expressed by the following parameters: the parameter α determined the curve shape or slope, the compressed threshold BPP_L, and the highest objective quality $SSIM_H$ that compressed image can achieve. Actually in image compression, image compression quality need to be able to achieve a certain human satisfaction, namely that the image quality can have certain distortion, but this distortion effect cannot affect the human eye to obtain important information of image, therefore, it is necessary to restrict the offline threshold $SSIM_L$ of image quality , making the image compression process effective. Finally, the quality perception model of image compression is:

$$SSIM=(bpp_L,\alpha,SSIM_H,SSIM_L) \tag{5}$$

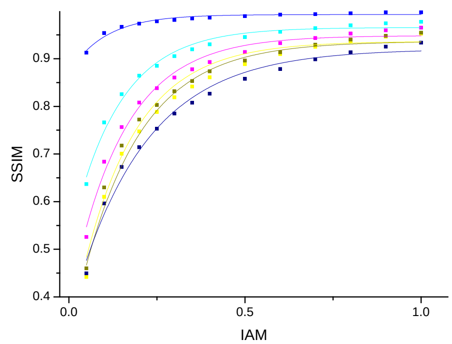
Observe the curve of compression regularity in figure 6 and figure 7, exponential function can be used as fitting function, and the fitting function of compressed quality of underwater image can be as follow type [20] :

$$SSIM=(SSIM_H-SSIM_L)(1-e^{-\alpha(bpp-bpp_L)})+SSIM_L \tag{6}$$

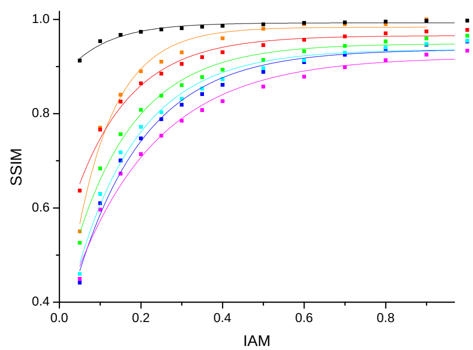
When the SSIM value of the image is around 0.8, the image quality will be slightly blurred, but the approximate texture information can be restored, so the lowest acceptable compression quality can be taken as $SSIM_L=0.8$. Then performed the QV parameter fitting to the underwater images in figure 5, and the corresponding fitting curves and fitting parameters are shown in figure 9 and table 3 respectively.

Table 3 The quality vector fitting parameters of underwater image compression

		SPIHT Compression			Adaptive CS compression		
image	IAM0	α	BPPL	SSIMH	α	BPPL	SSIMH
IMG20	7.3	9.59	-0.05	0.99	35.74	0.08	0.99
IMG9	16.8	7.25	0.14	0.97	10.34	0.13	0.98
IMG19	25.8	6.59	0.20	0.95	9.09	0.16	0.98
IMG6	35.7	5.87	0.26	0.94	8.23	0.20	0.98
IMG7	45.2	6.34	0.24	0.94	9.43	0.19	0.97
IMG3	50.1	4.89	0.32	0.92	7.80	0.22	0.96



(a)SPIHT compression fitting



(b)Adaptive CS compression fitting

Fig.9 fitting curve of Image compression quality

In figure.9, scatters are the actual quality of compressed image, the curves are compression quality perception fitting curves after the exponential fitting, It can be seen from the figure 9 that for each image can be fitting well and errors are small, showing the effectiveness of the fitting model. After obtaining the QV parameters of image compression quality, the image compression quality under any compression ratio can be obtained according to the fitting formula, and its process diagram is shown as figure 10, firstly calculate the IAM_0 values of the input image, and calculate the corresponding QV parameters, then can obtain the image compression quality estimation formula of corresponding image, finally plugging in BPP into the formula can estimate the compression quality.

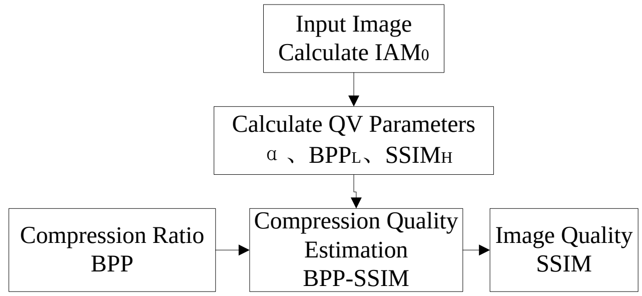


Fig.10 Image compression quality estimation process

B. QV parameter of fast estimation

There is a one-to-one correspondence between the QV parameters of an image, compression quality can be concluded after obtaining the QV parameters, but multiple QV parameters generally is difficult to get, need to do a lot of the fitting. 100 images are selected to fit the quality parameters, and the scatter points between the fitting parameters and the images IAM0 are obtained, a single image is selected in each IAM_0 ranges , and the scatter points are shown in figure 11. Observe figure 11 can found that there is also one to one correspondence between the QV parameters and IAM_0, in fact the quality curve of each image is associated with the activity of the image, quality curve with smaller IAM_0 tend to stable faster, its slope is smaller, the compression ratio will also be smaller under the same quality, the highest compression quality is bigger, so the fitting parameters can be estimated based on the IAM_0 of image, then obtain the compression quality.

Through figure 11, it can be observed that the parameters have a linear relationship, so the parameters are fitted by as formula :

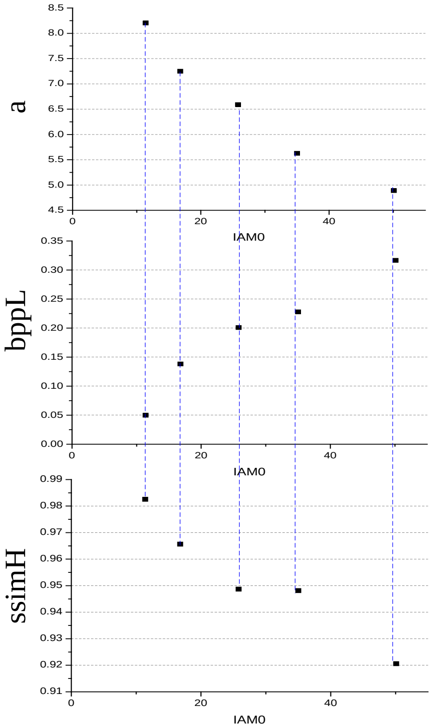
$$y=\sum_{k=0}^{n} b_k x_k = b_0 + b_1 x + b_2 x^2 + \cdots + b_n x^n \qquad (7)$$

Where b_k is constant.

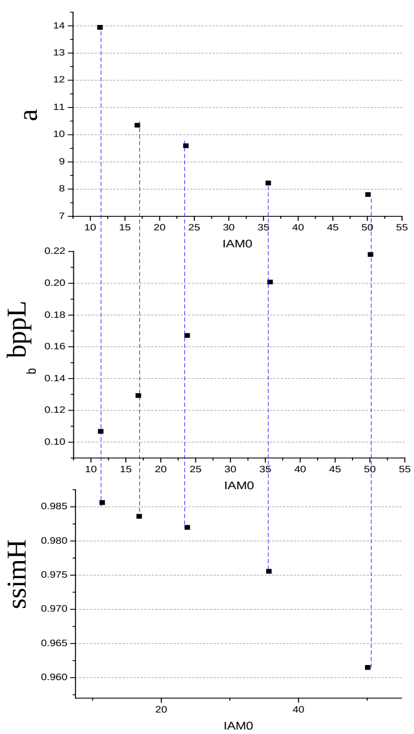
Take the first two items to fit $SSIM_H$ and BPP_L, take the first three items to fit α . The fitting scatter diagram as shown in figure 11, figure 12 respectively, and the fitting results of CS compression SPIHT compression are as follow:

$$\begin{cases} SSIM_{H\text{-SPIHT}} = 0.9913 - 0.0013 \times IAM_0 \\ \alpha_{\text{SPIHT}} = 9.5030 - 0.1190 \times IAM_0 + 0.0008 \times IAM_0{}^2 \\ BPP_{L\text{-SPIHT}} = 0.0283 + 0.0054 \times IAM_0 \end{cases} \qquad (8)$$

$$\begin{cases} SSIM_{H-CS} = 0.9949 + 0.00157 \times IAM_0 \\ \alpha_{CS} = 4.8045 - 0.0731 \times IAM_0 + 0.0004 \times IAM_0{}^2 \\ BPP_{L-CS} = 0.0117 + 0.0157 \times IAM_0 \end{cases} \qquad (9)$$

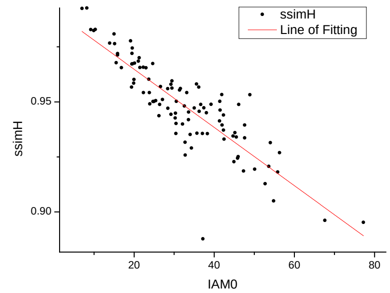


(a)SPIHT compression fitting

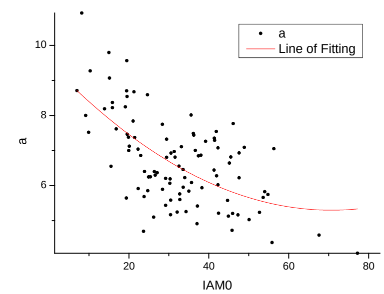


(b)Adaptive CS compression fitting

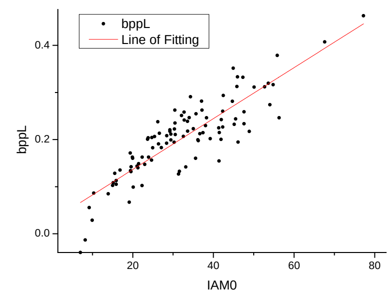
Fig.11 Scatter diagram of compression quality fitting parameters



(a) $SSIM_H$ scatter and fitting curve

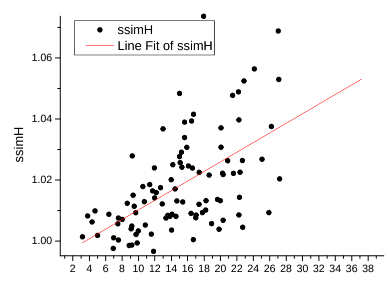


(b) α scatter and fitting curve

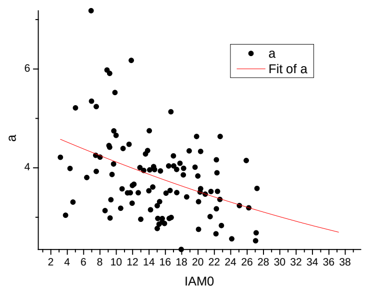


(c) BPP_L scatter and fitting curve

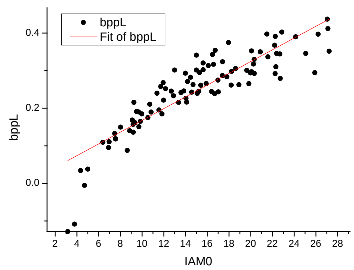
Fig.12 Quality fitting parameter scatter and fitting curves of SPIHT compression



(a) $SSIM_H$ scatter and fitting curve



(b) α scatter and fitting curve



(c) BPP_L scatter and fitting curve

Fig.13 Quality fitting parameter scatter and fitting curves of adaptive CS compression

There are some differences in the fitting effect of the parameters, but the final estimation error is within the allowable range. Through fast estimation of QV parameters, after inputting each image, IAM_0 can be calculate, and a set of QV parameters are obtained according to the linear relationship among the QV parameters and image activity measurement, thus the image compression quality BPP-SSIM curve is obtained , and then the the image quality can be estimated. The whole process not require to encode for image, under the condition of known the compression ratio, image compression quality is estimated by mapping directly.

C. Image compression with fixed value perception quality

In the process of image compression, the compression ratio is set generally based on channel condition, and unable to forecast image quality, which can bring the problem that image quality can't meet the demand of the human eye perception after coding compression and transmission, if image compression ratio can set according to perception quality, the above situation can be avoided, thus each image is compressed effectively with high quality. Then the above compression estimation formula will be able to solve the problem after the inverse mapping.

After obtain the relationship between image quality and compression ratio, image quality can be estimated through compression ratio, on the contrary, image compression rate can be calculated according to the required quality of compressed image in image transmission system. According to type (6), the relationship between BPP and SSIM can be obtained as follows:

$$BPP = BPP_L - \frac{\ln\left(1 - \dfrac{SSIM - SSIM_L}{SSIM_H - SSIM_L}\right)}{\alpha} \tag{10}$$

Where BPP_L, $SSIM_H$, α can be obtained according to the linear relation between the image and the image .

In order to meet the accurate application of compressed image quality, the linear interpolation method is proposed in reference[21], the accuracy of the estimation formula is further improved by no more than twice image coding and decoding processing, and its process diagram is as shown figure14. Firstly, calculate BPP_1 and its corresponding actual perception quality Q_1, if Q_1 and the desired compression quality Q are in an acceptable precision error range, there is no need for a second calculation, the final compression ratio $BPP_0 = BPP_1$; If Q_1 is greater than the error range, perform the interpolation calculation, when $Q_1 > Q$, the second compression ration is set as $BPP_2 = BPP_1 - \Delta BPP$; when $Q_1 < Q$, the second compression ration is set as $BPP_2 = BPP_1 + \Delta BPP$, ΔBPP is a small step compression ratio for interpolation, then calculate the actual quality Q_2 of image compressed by the interpolation compression ratio. the final precise compression rate after interpolation is as follow:

$$BPP_0 = \frac{Q - Q_1}{Q_2 - Q_1} \times \left(BPP_2 - BPP_1\right) + BPP_1 \tag{11}$$

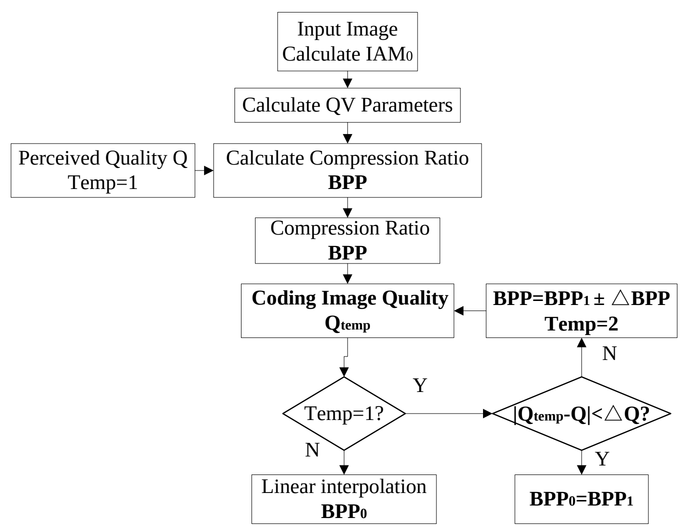


Fig.14 Linear interpolation flowchart of fixed value compression

V. Experiments

A. Verification of quality estimation model

In order to analyze the performance of the quality estimation formula in ⅣB, 110 underwater optical images are selected for the estimation analysis. Firstly, the IAM_0 of the image is calculated respectively, according to the type (8) and type (9), the SPIHT compression, CS compression curve parameters of corresponding images are calculate respectively, and then the obtained parameters are plugged into the type (6) to obtain the image compression quality fitting function. The compression quality value is predicted by substituting the independent variable BPP into the fitting function. The comparison of the estimation curve with the actual compression curve of three images is shown in figure 16, where the black curve is the actual compression curve and the red curve is the estimated curve. It can be seen from the figure that the quality value obtained by the compression estimation is similar with the actual compression value . The error distribution between the estimated value and the actual value of the 110 images at BPP from 0.05 to 1.0 is summarized as shown in figure 17.

In figure.16, the difference between the image estimation quality curve and the actual compression curve is small, which fully demonstrates the effectiveness of the estimation model and the estimation parameters. As shown in figure 16, when the compression ratio is greater than 0.2, the error between the predicted value of the image compression quality and the actual value does not exceed 0.05, and when the compression ratio is less than 0.2, the compression quality error of the image is in the range of -0.15 to 0.1, but when BPP<0.2, the majority of the image compression quality SSIM<0.8, the image reconstruction effect is poor, this quality range of the reconstructed image is generally not used, so the quality estimation of compressed image in this BPP range does not affect the estimation model in the use of estimation model in the actual image transmission, which also has the accuracy and practicality.

B. Experiment of compression quality with fixed value

Assume that in the channel transmission process need to obtain the compressed image which quality SSIM is equal to 0.90, that means set the required quality value as 0.9, select three different images randomly, obtain the corresponding compression ratio BPP according to type (10) and calculate the precise compression ratio by the interpolation method, and verify the actual compression quality under this two compression ratio. In the interpolation method, in order to obtain more accurate compression quality, the error threshold set as $\Delta Q = 0.0125$ and the compression rate step set as $\Delta BPP = 0.1$. The list of parameters obtained by the verification is shown in Table 4, and the SPIHT compressed image obtained before and after the interpolation is shown in figure 18.

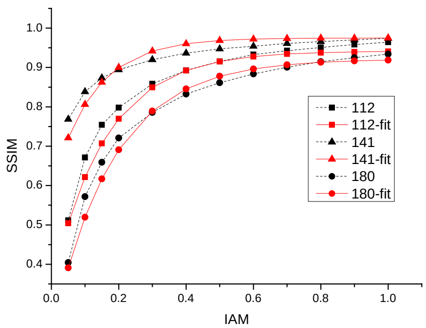
Table 4 The compression ratio and the actual quality when image quality in fixed value

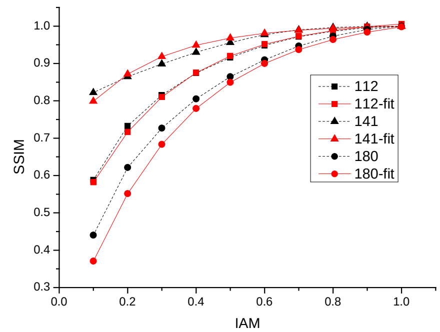
type	image	IAM0	bppL	α	ssimH	Calculate directly		Interpolation calculation	
						bpp1	SSIM1	bpp0	SSIM0
SPIHT	IMG119	21.455	0.144	7.338	0.963	0.274	0.860	0.394	0.898
	IMG147	32.167	0.202	6.547	0.949	0.373	0.936	0.211	0.889
	IMG156	63.000	0.369	5.349	0.908	0.853	0.938	0.548	0.891
CS	IMG119	21.455	0.174	4.093	1.011	0.331	0.929	0.266	0.903
	IMG147	32.167	0.216	3.922	1.015	0.222	0.920	0.204	0.910
	IMG156	63.000	0.478	3.018	1.041	0.445	0.938	0.353	0.902

As can be seen from the table 4, the compression ratio is obtained under the condition of fixed image quality. The difference between the actual compression quality and the specified quality is within the acceptable range, all are in the range of below 0.05. And the image quality can be obtained more accurately by the linear interpolation method, so that the compression image quality has higher accuracy. When the image quality corresponding to compression rate calculated directly is larger than the assigned quality, namely SSIM1>SSIM, the compression ratio is reduced by interpolation calculation. as in Figure 18(b)(c) is the SPIHT compression of IMG156, Figure 18.(b) is the image obtained by directly calculating with a compression ratio of 0.8529, Figure18.(c) is the image obtained by interpolating with a compression ratio of 0.5480. The quality of the two images is visually not significantly different, but the compression rate after interpolation is greatly reduced, so data transmitted in the system will be greatly reduced. so this image with complex texture can reduce its compression rate through calculating compression ratio by interpolation method, which effectively improve the efficiency of the image communication system while making the image quality is not affected. when SSIM1<SSIM, Interpolation calculation can improve the compression rate and improve the image quality, so that the reconstructed image quality is within the required accuracy range.

(a) IMG112 IAM0=37.46 (b) IMG141 IAM0=12.45 (c) IMG180 IAM0=53.07

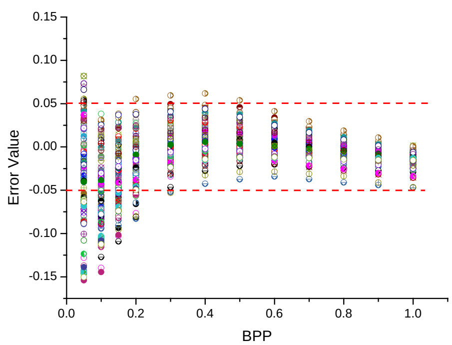
Fig.15 Underwater image for testing

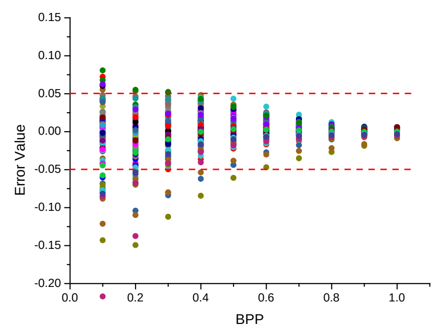




(a) SPIHT compression prediction (b)Adaptive CS compression prediction

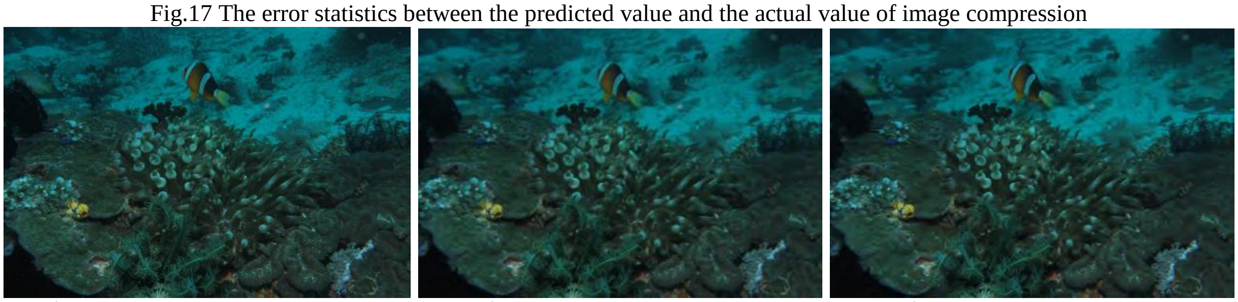
Fig.16 The comparison curve between the actual value and the predicted value of the compression quality (the black curve is the actual compression quality value, and the red curve is the fitting quality).





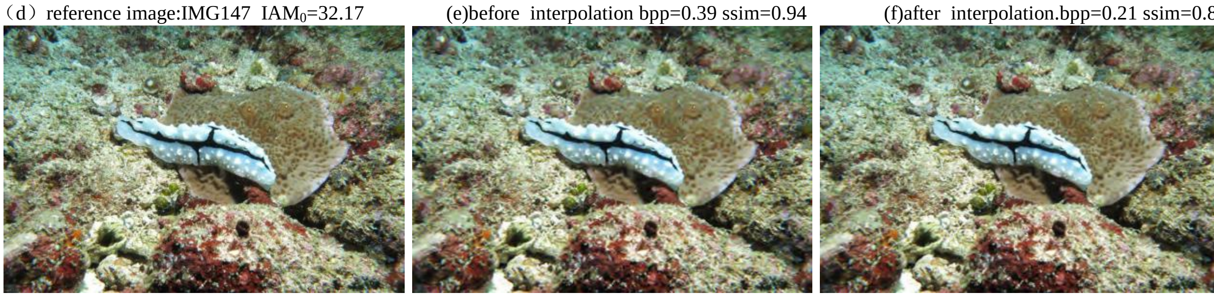
(a)SPIHT compression error (b)adaptive CS compression error

Fig.17 The error statistics between the predicted value and the actual value of image compression



(a) reference image:IMG119 IAM=21.45 (b) before interpolation bpp=0.27 ssim=0.86 (c) after interpolation. bpp=0.39 ssim=0.89

（d）reference image:IMG147 IAM_0=32.17 (e)before interpolation bpp=0.39 ssim=0.94 (f)after interpolation.bpp=0.21 ssim=0.89



（g）reference image: IMG156 IAM_0=63.0 (h)before interpolation bpp=0.85 ssim=0.94 (i)after interpolation.bpp=0.55 ssim=0.89

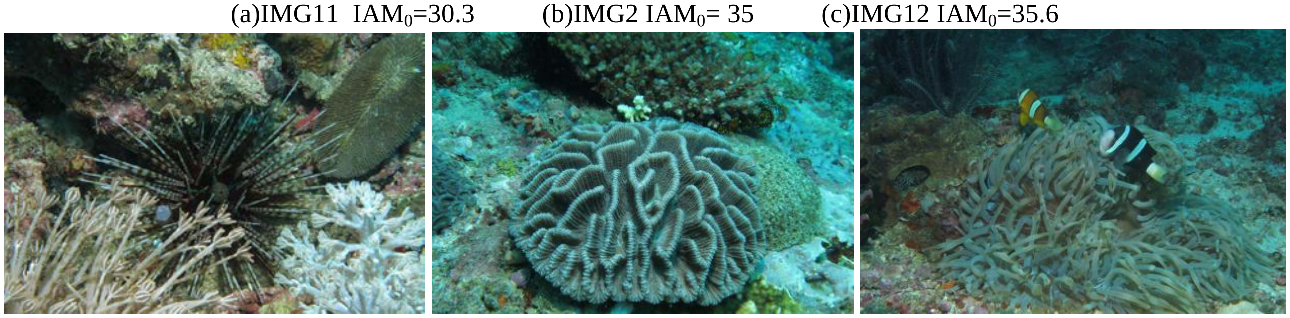
Fig.18 Image compression quality comparison before and after interpolation

VI. Conclusion

The image activity measurement IAM can measure the texture complexity of the image and has a close relationship with the image compression quality. In this paper, firstly the rules of the compression quality of the underwater optical image under different compression methods and the distorted characteristics of image compression are summarized . Then QV method is used to analyze and evaluate the image quality. By using the image quality prediction formula, corresponding image quality can be calculate without coding, so on the one hand it can guarantee the quality of compressed image, on the other hand, the prediction results can be used to guide the encoding strategy choice, determine coding parameters, etc. In addition, using the inverse function prediction formula, the relationship between image compression ratio and it compression quality is obtained, by using linear interpolation improvement scheme to further improve the accuracy of image compression quality.

Appendix: underwater images with similar IAM_0

(a)IMG11 IAM_0=30.3 (b)IMG2 IAM_0= 35 (c)IMG12 IAM_0=35.6



(d)IMG6 IAM_0=35.7 (e)IMG13 IAM_0= 37.1 (f)IMG1 IAM_0=41.3

(g)IMG17 IAM_0=41.6 (h)IMG4 IAM_0= 41.9 (i)IMG7 IAM_0=45.2

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