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A Customized Framework to Recompress Massive Internet Images

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Abstract Recently, device storage capacity and transmission bandwidth requirements are facing a heavy burden on account of massive internet images. Generally, to improve user experience and save costs as much as possible, a lot of internet applications always focus on how to achieve appropriate image recompression. In this paper, we propose a novel framework to efficiently customize image recompression according to a variety of applications. First of all, we evaluate the input image's compression level and predict an initial compression level which is very close to the final output of our system using a prior learnt from massive images. Then, we iteratively recompress the input image to different levels and measure the perceptual similarity between the input image and the new result by a block-based coding quality method. According to the output of the quality assessment method, we can update the target compression level, or switch to the subjective evaluation, or return the final recompression result in our system pipeline control. We organize subjective evaluations based on different applications and obtain corresponding assessment report. At last, based on the assessment report, we set up a series of appropriate parameters for customizing image recompression. Moreover, our new framework has been successfully applied to many commercial applications, such as web portals, e-commerce, online game, and so on.

Keywords massive internet image, image recompression, image quality assessment

1 Introduction

Along with the development of network and multimedia techniques, more and more information on internet is demonstrated and propagated in the form of picture. Based on internet images, many techniques have been developed[1-5]. Generally, a lot of commercial applications always focus on how to improve user experience and save costs as much as possible by recompressing massive internet images. In these applications, the rapid growing number of images and their increasing resolution make a heavy burden on the device storage capacity and transmission bandwidth requirements; it is still difficult to customize their appropriate file size and perceptual quality according to a verity of applications. Therefore, based on massive internet images, it is very important to sufficiently reduce the file size of images and meanwhile efficiently achieve the recompression customization for different applications.

For decades, a lot of methods have been proposed for image compression, which can reduce the file size of images without severely affecting their quality, such as the Joint Photographic Experts Group (JPEG) standard[6], JPEG 2000 standard[7], and other techniques[8-12]. Based on different image coders, these techniques try to use as small storage space as possible to represent image information. Among the compression techniques, the JPEG base line algorithm is widely used in many digital image applications. Most of images on internet belong to JPEG image format due to its higher compression quality and efficiency. Therefore, we can mainly focus on how to recompress the massive JPEG images in order to further reduce their file size.

On the other hand, image recompression also aims to preserve perceptual quality of images using image qua-

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lity assessment (IQA), which can accurately evaluate the quality performance of image compression. Recently, many IQA methods have been proposed, which can be divided into two categories: objective assessment and subjective evaluation. Objective assessment[13-16] is to develop quantitative measures that can automatically evaluate image quality in a perceptually consistent manner. Subjective evaluation[17-21] is to directly judge image quality by human beings, which is more accurate and reliable for IQA. Therefore, we can employ objective assessment to automatically evaluate recompression results and also organize subjective evaluation to verify and adjust recompression settings.

On basis of image compression and quality assessment, we present a novel framework that can not only sufficiently reduce the file size without perceptual quality loss but also efficiently customize image recompression for different applications. This framework can adaptively combine image compression techniques with quality assessment methods for each application. It mainly includes six components: initialization, image re-coding, quality measure, pipeline control, subjective evaluation, and custom service. Moreover, we have applied our framework to many commercial applications using two deployment strategies, such as web portals, e-commerce, online game, and so on. For example, in the Yixun e-commerce application, the verification result shows that our framework can reduce the file size of 305 988 images by 47.067% without changing their perceptual quality, and meanwhile save the transmission bandwidth and the page loading time by 25% and 20% respectively. A preliminary version of this paper appeared in [22].

After a brief review of related work in the next section, we elaborate our novel recompression framework and its six main components in Section 3 and Section 4 respectively. Then, two deployment strategies and several representative applications are introduced in Section 5. Finally, the conclusion and discussion about this paper are given in Section 6.

2 Related Work

2.1 Image Compression

Image compression plays an important role in digital image processing because uncompressed photos require considerable storage capacity and transmission bandwidth. Although rapid progress has been made in technologies such as processor speeds, mass-storage density, and digital communication system, demand for data storage capacity and data transmission bandwidth still outstrip the capabilities of these technologies.

For still image compression, JPEG standard[6] has been established by ISO (International Organization for Standardization) and IEC (International Electrotechnical Commission). Since the JPEG standard was established, the JPEG base line algorithm has been widely used in many digital imaging applications. This is mainly due to the free and efficient software that is available from the Independent JPEG Group (IJG)①[7]. In March 1997, a new call for proposals was launched for the development of a new standard for the compression of still images, the JPEG 2000 standard. The JPEG 2000 standard which was issued in six parts adopts a wavelet decomposition approach as its backbone.

Recently, many techniques have been introduced into the context of image compression. Based on image inpainting techniques, [23] proposes an image compression framework towards visual quality rather than pixel-wise fidelity. Machine learning based approaches[10,24] have been proposed to do lossy image compression. These approaches learn a model from a few representative pixels and predict color on the rest of the pixels. But from a market perspective, it would be impossible to allocate methods which require a non-standard image decoder.

Since the JPEG base line algorithm is widely used in many digital imaging applications, as we mentioned before, and JPEG decoding is already built into many devices, including DVD players, televisions, cellular phones and personal computers, etc., it is very important for any method for reducing the image file size to produce a file that is fully compatible with the baseline JPEG standard[6], to ensure its successful display on any device.

2.2 Image Quality Assessment

Image quality assessment (IQA) plays a fundamental role in the design and evaluation of imaging and image processing systems, such as those for compression, enhancement, restoration. As an example, in our system, IQA algorithms can be used to systematically evaluate the performance of different image compression algorithms that attempt to minimize the number of bits required to store an image, while maintaining sufficiently high image quality.

Since images are finally judged by human beings, subjective evaluations are considered to be the most reliable way to assess image quality. A significant effort has been done in the field of subjective image quality assessment[17-18]. Sheikh *et al.* in [19] presented an extensive subjective quality assessment study and evaluated the performance of 10 image quality assess-

①Independent JPEG group (IJG), http://www.ijg.org ment algorithms. The authors also made their dataset publicly available[25]. There are also standards on subjective evaluation of image quality[20-21] including double stimulus impairment scale (DSIS), double stimulus continuous quality-scale (DSCQS), single stimulus (SS) and forced-choice double stimulus (FCDS). Although subjective evaluations are reliable to assess image quality, in practice they are usually too cumbersome, time-consuming, expensive; most importantly they cannot be incorporated into automatic systems that can adjust themselves in real time based on the feedback of output quality.

The interest in objective image quality assessment has been growing at an accelerated pace over the past decade[13-15,26]. The goal of research in objective IQA is to develop quantitative measures that can automatically predict the quality of images or videos in a perceptually consistent manner. According to the availability of an original or reference image, objective image quality metrics can be classified into three classes which are full-reference, reduced-reference and no-reference. We focus on the full-reference IQA in this paper.

Perhaps, the earliest image quality metrics are the mean squared error (MSE) and peak signal to noise ratio (PSNR) between the reference and distorted images. These metrics are still widely used for performance evaluation, despite their well-known limitations, due to their simplicity. Wang *et al.* in [27] reviewed advantages and disadvantages of MSE and reviewed emerging alternative signal fidelity measures. One recently proposed approach to image fidelity measurement, which may also be proven highly effective for measuring the fidelity of other signals, is the structural similarity (SSIM) index[13]. The SSIM approach was originally motivated by the observation that natural image signals are highly structured, meaning that the samples of natural image signals have strong neighbor dependencies which carry important information about the structures of the objects in the visual scene. SSIM actually takes a variety of forms, depending on whether it is implemented at a single scale[13], over multiple scales[28], in the wavelet domain[29], or used local information content based pooling[30]. Based on natural scene statistics, Sheikh *et al.*[31] proposed a novel information fidelity criterion approach for the problem of IQA. The visual signal-to-noise ratio (VSNR) metric, proposed by Chandler *et al.*[14], operates via a two-stage approach. It is computation efficient and requires less memory. If the type of distortions is known, then the design of full-reference IQA is quite straightforward. Based on the artifacts that will be introduced by JPEG image coder, Shoham *et al.*[16] proposed a perceptual image quality measure called BBCQ (block-based coding quality) which is composed of three components. These components are based on a pixel-wise error using PSNR, evaluation of added artifactual edges along coding block boundaries and a measure of texture distortion. These three measures are combined using a weighted geometric average[16].

3 Overview

We introduce a novel framework to efficiently customize image recompression according to a variety of applications. Fig.1 provides the overview of our framework. For each application based on massive internet images, our motivation is to save bandwidth and storage as much as possible under perceptually lossless compression.

First of all, we estimate the source compression level of an input image, and initialize its target compression level by a perceptual similarity prior. Secondly, we combine those two compression levels to compute a re-coding matrix and generate a new compression result. Thirdly, we measure the perceptual similarity between the input image and the new result by a block-based coding quality method. Fourthly, its output can be controlled into three available pipelines: 1) update the target compression level; 2) return the final recompression result; 3) change into the subjective evaluation. Fifthly, guided by each different application, we organize the corresponding subjective evaluation and obtain its assessment report. At last, based on the report, we customize the whole recompression for each application

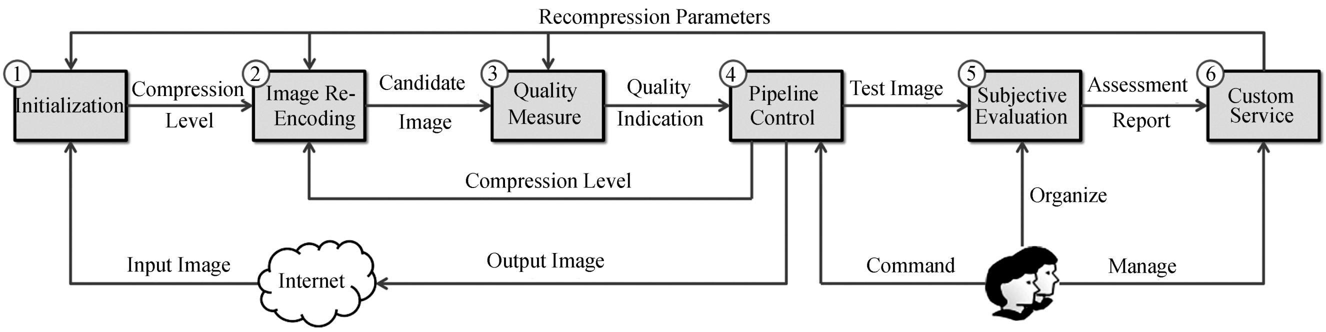


Fig.1. Overview of proposed framework.

by setting up a series of appropriate parameters.

Our framework can not only re-compress an image but also guarantee its perceptual consistency. Thus it can optimize the bandwidth and storage requirements for a lot of applications with massive internet images. In this paper, we propose its two kinds of deployment strategies and integrate it into some representative applications, such as portal website, e-commerce, online game, and so on.

4 Customized Recompression

In this section, we describe our new framework for customized recompression in detail, which includes six main components: initialization, image re-coding, quality measure, pipeline control, subjective evaluation, and custom service.

4.1 Initialization

Generally, in order to achieve the satisfying recompression, the optimal target compression level can be figured out by continuous iterations. Unfortunately, the immoderate iterations often influence the recompression performance severely. Therefore, for reducing the iteration number and improving the efficiency of recompression, we focus on how to initialize an appropriate target compression level according to a customized application.

On the basis of BBCQ[16], given a series of its default parameters, we first analyze the relationship between the compress level and the BBCQ's similarity score. As shown in Fig.2, we observe more than 5 000 internet images and construct a perceptual similarity prior, i.e.,

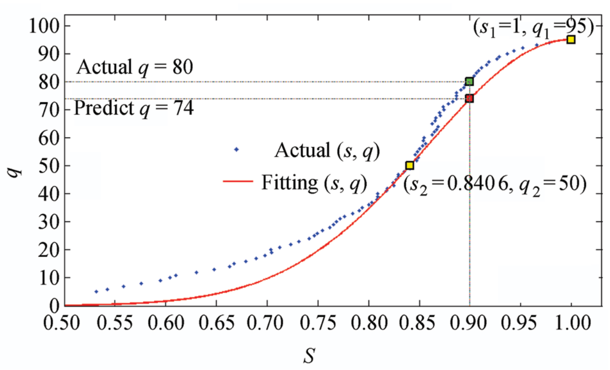


Fig.2. Quality-score fitting. The Quality-score distribution of one image can be fitted by a partial Gaussian distribution function; after two pairs of quality-score ($s_1 = 1.0, q_1 = 95$) and ($s_2 = 0.840\,6, q_2 = 50$) are initialized, we can predict the target compression level $q = Q(0.9) = 74$ using (4); based on the quality score threshold $s_t = 0.9$ and the initialized compression level $q = 74$, we can continuously update the target compression level until its optimal level $q^* = 80$.

the quality-score distribution of one image can be fitted by a partial Gaussian distribution function, which is defined as:

$$Q(s) = \frac{k}{\sqrt{2\pi}\sigma} \exp\Big(-\frac{(s-\mu)^2}{2\sigma^2}\Big), \tag{1}$$

where s is the BBCQ's similarity score; $Q(s)$ is the compression quality factor, also known as Q factor in the Independent JPEG Group (IJG); μ and σ is the mean and standard deviations of the quality-score distribution, and μ is fixed to 1.0; k is a scaling factor. If two pairs of quality-score are provided, we can subsequently compute σ and k, which are unknown in (1). Given $(s_1, Q(s_1))$ and $(s_2, Q(s_2))$, their division can remove k and solve σ, which is defined as:

$$\ln\frac{Q(s_1)}{Q(s_2)} = \frac{(s_2 - s_1)\times(s_2 + s_1 - 2.0)}{2\sigma^2}. \tag{2}$$

When σ is obtained by (2), we can further determine the corresponding quality-score distribution.

Obviously, for the above distribution function, we have to preliminarily compute two pairs of quality-score by BBCQ. Fortunately, according to an important observation: when s is 1.0, $Q(s)$ approximates to the source compression level of input image, we can efficiently avoid one of those two pairs by estimating its compression quality from the source image. Given the quantization matrix of the source image $\boldsymbol{M}_s$ and the baseline matrix $\boldsymbol{M}_b$, we can estimate the compression quality using their linear transformation, which is defined as:

$$Q(1) \approx \min_q \sum_i \frac{|M_q(i) - M_s(i)|}{M_b(i)}, \tag{3}$$

where q is the compression quality and $\boldsymbol{M}_q$ is its quantization matrix based on $\boldsymbol{M}_b$. According to (3), we can initialize one pair of quality-score $(s_1 = 1.0, Q(s_1))$. Moreover, given $Q = 50$, we can compute another pair $(s_2, Q(s_2) = 50)$ by BBCQ.

After obtaining two pairs of quality-score, we can produce the corresponding target compression levels for the different applications. Given the score threshold s_t of an application, the target compression level can be defined as:

$$\frac{Q(s_t)}{Q(s_1)} = \exp\Bigg(\frac{\ln\dfrac{Q(s_1)}{Q(s_2)}\times(s_1 - s_t)(s_1 + s_t - 2.0)}{(s_2 - s_1)(s_2 + s_1 - 2.0)}\Bigg), \tag{4}$$

where $Q(s_t)$ is the initialized target compression quality within s_t. As shown in Fig.2, after two pairs of quality-score $(1.0, 95)$ and $(0.840\,6, 50)$ are initialized, we can predict the target compression level $q = Q(0.9) = 74$

using (4). For most images, the differences between our predicted target compression levels and the final optimal compression levels are less than 8. That means if we set the increment step to 3, the iterations are typically reduced from 7, which are needed for binary search, to 3. This really makes our recompression framework efficient. Starting from the perceptual similarity prior, we can further find out the optimal compression quality by moderate iterations, which is described in the next subsections.

4.2 Image Re-Coding

Given a compression quality q, we can obtain a corresponding quantization matrix $\boldsymbol{M}$ according to IJG and quantize the input image with this quantization matrix. Quantization matrix $\boldsymbol{M}$ which indicates quantisation steps is an 8×8 matrix. Ordinarily, for smaller values of q, the quantisation steps in the quantisation table $\boldsymbol{M}$ are bigger, thus resulted in a lower quality output image; for larger values of q, the quantisation steps in the quantisation table $\boldsymbol{M}$ are smaller, thus resulted in a higher quality output image. However, many experiments have shown that the IJG quality rating scale is not perceptually monotone[32]. As shown in Fig.3, we regard Fig.3(a), which is a JPEG image with quality level of 75, as an input image in our framework. Then we recompress Fig.3(a) to quality level 50, and obtain Fig.3(b). Fig.3(a) is 19% smaller but has considerable visual grainy artifacts. But if we recompress the $q = 75$ image to $q = 48$, the grainy artifacts will disappear and result in a 36% smaller image, as shown in Fig.3(c). Compared with the $q = 50$ image, the $q = 48$ is perceptually much closer to the $q = 75$ image. This nonmonotonicity in the IJG quality rating scale can bring bad effects to our system, since part of our framework such as initialization and pipeline control require a monotonicity between quality and perceptual score.

Bauschke et al.[32] reported a novel heuristic for requantizing JPEG images by incorporating the Laplacian distribution of the AC (alternating current) discrete cosine transform (DCT) coefficients with an analysis of the error introduced by requantization. The output images of their algorithm are generally smaller and often have improved perceptual image quality over a "blind" requantization approach. Ng et al.[33] presented an algorithm to reduce the quantisation errors caused by applying multiple reduced Q-factor JPEG compression to a still image.

Here, we modify the quantization matrix $\boldsymbol{M}$ using heuristic algorithm proposed in [32]. Denote $\boldsymbol{M}_o$ and $\boldsymbol{M}_t$ to be the quantization matrix of the input image and the target quantization matrix, respectively. We want to modify $\boldsymbol{M}_t$ based on $\boldsymbol{M}_o$ to obtain a new quantization matrix $\boldsymbol{M}_n$ which is closed to $\boldsymbol{M}_t$ in order to requantize the input image. Denote the corresponding element of $\boldsymbol{M}_o$, $\boldsymbol{M}_t$ and $\boldsymbol{M}_n$ by o_{ij}, t_{ij} and n_{ij}, where i, j are the row and column index of the quantization matrix. The new n_{ij} is constructed as follows: first compute $k = \lfloor t_{ij}/o_{ij} \rfloor$, then define

$$n_{ij} = \begin{cases} o_{ij}, & \text{if } k = 0, \\ k \times o_{ij}, & \text{if } k > 0. \end{cases} \quad (5)$$

Using (5), we obtain a new quantization matrix $\boldsymbol{M}_n$ and compress the input image with this quantization matrix.

4.3 Quality Measure

For a new recompression image, we further measure its recompression quality by a block-based coding quality method (BBCQ), which can evaluate the degradation in image quality compared with the original image[16]. BBCQ is composed of three error components: pixel wise difference (PWD), added artifactual edges (AAE), texture distortion (TD). PWD defines the local errors calculated pixel-by-pixel; AAE defines the

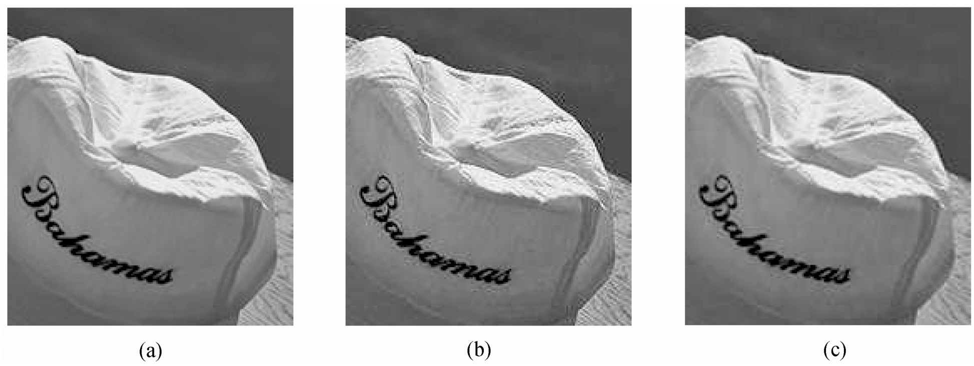


Fig.3. Nonmonotonicity of the IJG quality rating scale. (a) JPEG image with quality level $q = 75$. (b) Image recompressed to quality level $q = 50$ which has considerable visual grainy artifacts. (c) Image recompresed to quality level $q = 48$, where the grainy artifacts disappear. Compared with (b), (c) is perceptually much closer to (a).

discontinuities between adjacent blocks due to the independent coding of each $N\times N$ block; TD defines the loss of texture detail or over-smoothing due to coarse quantization of high frequency. On basis of PWD, AAE and TD, we can quantify the perceptual similarity between the new recompression result and the input image.

In order to obtain a single quality score, we combine the three above components using a weighted geometric average, which is defined as:

$$S_{\mathrm{BBCQ}} = (S_{\mathrm{PWD}})^{\alpha} \times (S_{\mathrm{AAE}})^{\beta} \times (S_{\mathrm{TD}})^{\gamma}, \quad (6)$$

where S_{BBCQ} is the BBCQ's score, S_{PWD}, S_{AAE}, S_{TD} are the three error components of BBCQ, which can refer to in detail; α, β, γ are fixed to 0.3, 0.35, 0.35 respectively for making these three error components almost equally important. For the higher robustness of BBCQ, we first divide the image into tiles, and compute the BBCQ's score of each tile. Next, we sort their tile scores and choose the n-th percentile result as the final BBCQ's score of the entire image. This method can efficiently increase the score robustness for different image sizes and contents. As shown in Fig.4, we compress the original image Fig.4(a) into different compression levels Fig.4(b), Fig.4(c), Fig.4(d) with quality 80, 55, 15 and their corresponding BBCQ's scores 0.898 6, 0.847 9, 0.667 7 respectively. Obviously, when compressing the original image with a lower quality, the compressed image will has more visual grainy artifacts, and the coding block grid is more visible.

4.4 Pipeline Control

After obtaining the recompression result and its quality score, we can control them into three available pipelines according to the different requirements, which aims to update the target compression level, return the final recompression result or change into the subjective evaluation.

Update the Target Compression Level. Given a quality score threshold s_t, we can initialize a target compression level $Q(s_t)$, which is estimated by (4). We next recode the source image with the compression level $q = Q(s_t)$, compute its BBCQ's score $S(q)$ and compare it with the threshold. If $S(q) > s_t$, update the target compression level $q = q - w$, and repeat the above operations until $S(q) < s_t$; if $S(q) < s_t$, update the target compression level $q = q + w$, and repeat the above operations until $S(q) > s_t$. In practice, we set increment step $w = 3$ because this setting reaches the optimal compression quality fast while restricting the error within 1. Finally, we can assume a local linear relationship and find out the optimal target compression level q^*. As shown in Fig.2, based on the quality score threshold $s_t = 0.9$ and the initialized compression level $q = 74$, we can continuously update the target compression level until its optimal level $q^* = 80$.

Return the Final Recompression Result. On basis of the optimal target compression level, we can further recompress the source image and return the final result. Fortunately, after compressing massive internet images, users can save a lot of bandwidth and storage for the related application. For example, we take Fig.4(a) as an input image of our framework and set $s_t = 0.9$. The output of our framework is Fig.4(b) with $q^* = 80$. These two pictures are perceptually identical.

Change into the Subjective Evaluation. Here, we collect the recompression results and organize the subjective evaluation in order to fix a series of appropriate

(a) (b) (c) (d)

Fig.4. JPEG images with different compression levels. (a) Source image. (b) Recompressed image with quality level $q = 80$. (c) Recompressed image with quality level $q = 55$. (d) Recompressed image with quality level $q = 15$. Their corresponding BBCQ's scores are 0.898 6, 0.847 9 and 0.667 7 respectively. Obviously, when compressing the original image with a lower quality, the compressed image will has more visual grainy artifacts, and the coding block grid is more visible.

recompression parameters, which can guarantee the recompression quality and meanwhile meet the bandwidth and storage requirements of different applications. The detailed introduction about the subjective evaluation will be described in the next subsection.

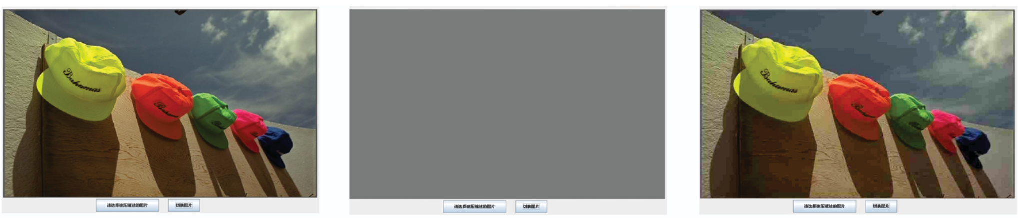
4.5 Subjective Evaluation

In order to evaluate the performance of our recompression system and guide each different application to reach its own compression level, we perform standardized subjective image quality assessment based on [20-21, 34]. In our framework for perceptually lossless compression, assessing thresholds of different application is required. Forced-choice double-stimulus (FCDS) method[20] which was specifically designed for assessing thresholds of visibility is suitable for this task. On the other hand, subjective assessment methods, such as double stimulus impairment scale (DSIS)[21], can be used to evaluate the perceptual quality of images by computing the mean opinion scores (MOS) from human ratings. In our framework of high compression levels we take this subjective evaluation to evaluate the perceptual quality of the output images. According to different applications, we classify our subjective evaluations into two categories.

The first subjective evaluation is designed for perceptually lossless compression level. Excepting lossless compression, which has no need to do subjective evaluation since there is nothing changed in pixel domain, perceptually lossless compression level is the lowest compression level in our framework. Perceptually lossless compression which is suitable for many applications is the most typical application of our framework. Here, we present our subjective evaluation for perceptually lossless compression level. The testing follows the FCDS method.

The second subjective evaluations is designed for high compression levels. We do standardized subjective testing based on DSIS[21]. Our setting for this subjective evaluation is similar to the subjective evaluation for perceptually lossless compression level. But here the original image always shows up in the first order and the recompressed one shows up in the third order. The observers were told that before testing. Observers do not need to decide which of the pictures is the impaired one, instead, they are asked to rank the quality of the recompressed image using a standard 5-step impairment scale, as shown below: 5 — imperceptible, 4 — perceptible, but not annoying, 3 — slightly annoying, 2 — annoying, 1 — very annoying.

For instance, we organize a subjective evaluation for a website application under perceptually lossless compression. 20 testers (8 of which are female) participate in this subjective evaluation. The average age of the testers is 25.0. The testing are performed using identical Microsoft Windows workstations. In each testing session, the observers are presented with a series of triple pictures which are composed of an original picture, a picture recompressed by our framework and a gray image. The gray image is used to eliminate human vision residuals. The original picture and the compressed picture are shown in random order and the gray image is always shown between these two pictures. All the pictures are shown at full resolution. If the resolution of the picture is higher than the screen resolution, we will cut the picture into many parts so as to show each portion of the picture at full resolution. The observers are able to switch among the triple images as many times as they desire, and then have to decide which of the pictures is the impaired one. As shown in Fig.5, a web-based interface showing the image to be compared and a Java button applet for choosing the impaired one is used. The workstations are placed in an office environment with normal indoor illumination levels as the same in [19]. All other testing procedures such as selecting the observers and instructing observers are performed in accordance with [20]. Each tester views 50 test image pairs which were randomly selected from a large image database. Therefore, a total of 1 000 image pairs are viewed in this subjective evaluation. For 52.9% of the test image pairs the recompressed image is correctly chosen. If both images are identical the expected distribution is 50%. And the 95% confidence interval for our test of 1 000 image pairs is [46.9, 53.1].



(a) (b) (c)

Fig.5. Subjective evaluation tool. The left button is used to choose this picture as the impaired one; and the right is used to switch among images. (a), (b) and (c) are three different pages corresponding to the source image, gray image and recompressed image. The gray image is used to eliminate human vision residuals.

Our results lie within the 95% confidence interval, i.e., one cannot tell the difference between the original image and recompressed image.

4.6 Custom Service

On basis of the subjective evaluation, we can provide the appropriate custom service for each different application. First of all, for a new application, we try to find a similar application from a database in which a lot of operational applications are recorded completely. Secondly, we extract a series of parameters from the similar application information to initialize the whole recompression. Thirdly, after image recompression, we achieve the subject evaluation to verify the effectiveness of recompression parameters. Fourthly, according to the assessment report, we iteratively adjust the parameters until the assessment report can meet the application requirements. Finally, we finish the custom service for the application and write its information into the database.

For example, as a new mode of e-commerce, the group purchase application can match to the traditional business-to-customer (B2C) application for custom service. Thus we first initialize the recompression parameters of the group purchase application using the information of the traditional B2C application. We next execute the image recompression and collect the results for subject evaluation. Then we analyze the assessment report and consider the specific quality, bandwidth and storage requirements of the group purchase application to continuously update the parameters. At last we customize the whole recompression for the group purchase application and record its information into the database.

5 Deployment and Application

5.1 Deployment Strategies

To efficiently recompress massive internet images using our new recompression framework, we further propose two deployment strategies: online service and offline service.

5.1.1 Online Service

Online service can provide the real-time recompression feedback for a certain application. For example, the online service is more suitable for most of CMS websites because they often require to synchronously update web information in the process of recompression. Therefore, we usually employ this kind of deployment strategy in some instant scenarios where images are re-compressed on every call. As shown in Fig.6, its flow is described as follows:

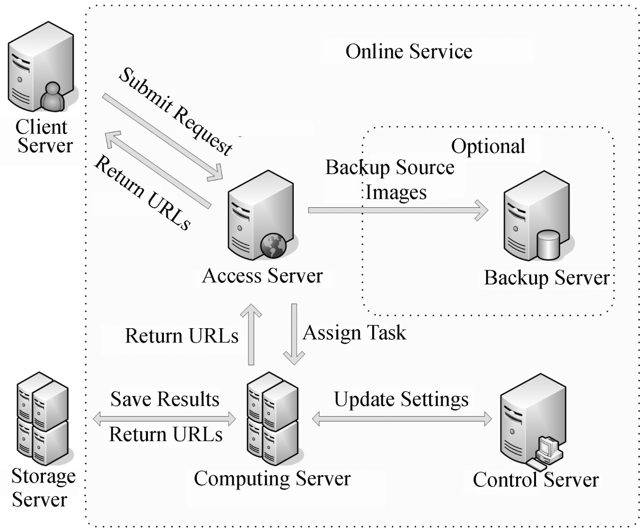


Fig.6. Online service can provide the real-time recompression feedback for a certain application.

1) The client server submits a request forwards to the access server.

2) The access server optionally forwards source images to the backup server for error recovery.

3) The access server assigns an adequate amount of recompression tasks to the computing server according to load balancing.

4) The computing server achieves image recompression according to the settings of the control server.

5) The computing server distributes the recompression results to the storage server and obtains their URLs.

6) The computing server returns these URLs to the access server.

7) The access server returns the recompression results (URLs) to the client server.

5.1.2 Offline Service

Compared with online service, offline service can provide the non-realtime recompression feedback for a certain application. For some storage applications, the online service cannot recompress massive images simultaneously due to restricted computing capability. Thus we employ offline service to complete recompression with load balancing. As shown in Fig.7, its flow is described as follows:

1) The client server submits a request to the register server.

2) The register server adds a scheduled task to the scheduling server, which can balance all scheduled tasks.

3) The scheduling server optionally forwards source images to backup server for error recovery.

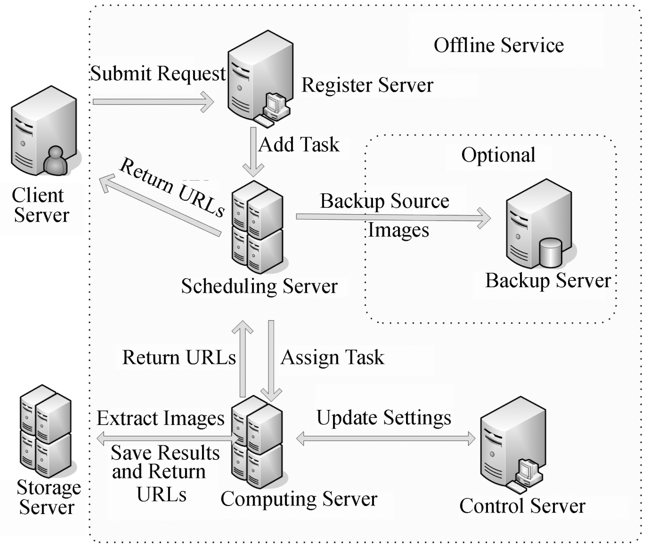


Fig.7. Offline service can provide the non-realtime recompression feedback for a certain application.

4) The scheduling server assigns an adequate amount of recompression tasks to the computing server according to load balancing.

5) The computing server extracts source images from the storage server and achieves image recompression according to the settings of the control server.

6) The computing server distributes the recompression results to the storage server and obtains their URLs.

7) The computing server returns these URLs to the scheduling server.

8) The scheduling server returns the recompression results (URLs) to the client server.

5.2 Representative Applications

The customized recompression framework introduced in the previous section can be used to effectively reduce the file size of images for a wide variety of applications. Three typical applications are discussed in the sequel: online service for Instant Messaging (IM), offline service for perceptually lossless compression, and offline service for higher compression.

Direct benefits from reducing the file size of images are to save device storage capacity and transmission bandwidth requirements. Furthermore, less page loading time is needed for images with small file size. This will improve user experience and bring more visitors to visit web portals. The monitoring data shows that the transmission bandwidth and the page loading time are reduced by 25% and 20%, respectively. We believe that along with the popularization of our system we can reduce the cost of the bandwidth by 30 million RMB every year.

Online Service for Instant Messaging. To save bandwidth, many Instant Messaging tools have an upper bound file size for transferred image. If the file size of the transferred image surpasses the upper bound, the backend server will compress the transferred image to a constant level or resize the transferred image into low spatial resolution to reduce the file size of the transferred image. However both operations have disadvantages. Compressing the transferred image to a constant level will affect the perceptual quality of image sometimes, and sometimes it will not reach the highest possible compression level. Image downsampling will change the spatial resolution of the image and this is apparently beyond the expectation of the user. Our online service can provide almost real-time perceptual lossless recompression for Instant Messaging tools. In most cases the file sizes of our output images are smaller than the upper bound. In the case of super high resolution images, our perceptually lossless compression result may not meet the specifications and we will do further image downsampling.

Offline Service for Perceptually Lossless Compression. The online service cannot handle massive images instantly since the computing capability of the backend server is limited. And many applications do not require a real-time recompression. We can just compress images in the device storage when our backend server has surplus computing capability. In fact, we have applied our offline perceptually lossless compression to a number of applications, such as web portals, e-commerce, and online game. Table 1 shows the performance of our offline service for perceptually lossless compression on three typical applications. The second row of Table 1 shows that the compression ratio of our framework applying to Yixun e-commerce is up to 47.067%. However, the compression ratios in the third row and the fourth row are not so high as the compression ratio in the second row. This is mainly because that the input images of these two applications have already been highly

Table 1. Framework Performance of Offline Service for Perceptually Lossless Compression on Three Applications

Applications	No. Total Images	Running Time (s)	Average Running Time (s)	Original Total File Size	Total File Size After Compression	Compression Ratio (%)
Yixun e-commerce	305 988	16 527.04	0.054	13.67 GB	7.24 GB	47.067
Huyu online game	207 428	16 410.02	0.079	9.54 GB	7.40 GB	22.420
Tencent AdCenter	2 752	245.12	0.089	142.26 MB	111.93 MB	21.319

compressed. The average running time is less than 0.1 second that indicates the efficiency of our framework.

Offline Service for Higher Compression. Some applications, for example SOSO map②, need higher compression level (i.e., smaller file size) instead of high image quality. There is a trade-off between compression level and image quality. In order to find this equilibrium point of specific application, we gradually increase our compression level by changing corresponding parameters, such as parameters in Subsection 4.3 and typically s_t which was mentioned in Subsection 4.1. And then we use these new parameters to recompress our image training set and do subjective evaluation on the set. Our offline service for higher compression has applied to SOSO map. We recompress more than 13 TB images in SOSO map and get 10% more compression ratio than the original method which recompresses the images into a const compression level, yet having better perceptual quality than the original method.

6 Conclusions and Discussion

In this paper, a novel customized recompression framework for massive internet images was proposed. Using a prior knowledge on compression level and perceptual quality score, the efficiency of our framework are guaranteed by predicting an exact initial compression level for our iterative recompression. Application-based subjective evaluations effectively customize the most appropriate recompression for each different application by finding a trade-off between the image file size and image perceptual quality.

We have applied our framework to many applications, such as web portals, e-commerce, online game. Subjective evaluation results and monitoring data indicate that perceptually lossless compression in our framework reduced the file size of massive images by about 50% without changing their perceptual quality. This apparently saves storage and transmission bandwidth requirement and improves user experience.

Our framework only takes JPEG images as input, but there are still many PNG, BMP, or GIF pictures on the internet. In the future, we plan to further generalize our framework so that it can handle more images with different image formats.

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②http://map.soso.com/

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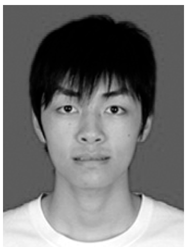

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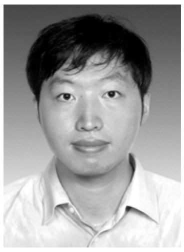

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