The following manuscript was published in

Image Quality Measurement Based on Statistics of Activity Regions

Yung-Sheng Chen* and Fan-Chang Meng

Department of Electrical Engineering, Yuan Ze University
135 Yuan-Tung Road, Chung-Li 320
Taiwan, Republic of China
TEL: +886-3-4638800 (ext. 409)
FAX: +886-3-4639355
E-MAIL: eeyschen@ee.yzu.edu.tw

*Author to whom correspondence should be addressed.
# List of Figures

1. Original images. ................................................................. 12
2. (a) Original MOON Image (11). (b) Labeled blocks (called activity regions) with $T = 10$. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. ................................................................. 13
3. (a) Original image of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. ................................................................. 14
4. (a) Original image of Image (24). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. ................................................................. 15
5. Relationship between total score (objective evaluation) and grade (subjective evaluation) obtained with 504 observations. Here we have $\theta_1 = 30$, $\theta_2 = 43$, $\theta_3 = 57$, and $\theta_4 = 70$, respectively. ................................................................. 16
6. Original images are reshown in descending sequence of computing scores by the proposed approach. ................................................................. 17
7. (a) Linear motion blur version ($L = 11$, $\phi = 0$) of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. ................................................................. 18
8. (a) Gaussian blur version ($\sigma = 1.8$, $W = 7$) of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. ................................................................. 19
9. (a) Sharpened version ($A = 1.3$) of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. ................................................................. 20
10. (a) Sample-reduced version (128×128) of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. ................................................................. 21
11. Performance comparisons, where abscissa and ordinate represent the image number (from 1 to 24) and the corresponding image score, respectively. (a) Original images vs. the linear motion blur versions. (b) Original images vs. the Gaussian blur versions. (c) Original images vs. the sharpening versions. (d) Original images vs. the sample-reduced versions. ................................................................. 22
12. Illustration of image scores affected by adding random noise. This comparison shows that the higher the degree of random noise added, the higher the image score is. ................................................................. 26
List of Tables

1  Illustration of image scores from enlarging the images. . . . . . . . . . . 26
ABSTRACT

Image restoration is a well-known technique for dealing with images that have been recorded in the presence of one or more sources of degradation. However, why do we want to perform image restoration upon a given image? Who can tell us the image quality is good or needs to be processed? In this paper, based on the activity regions of a gray image, we present an approach to performing both objective and subjective evaluations for measuring image quality. Four versions of an image are transformed, and the results obtained by the proposed approach are used for comparisons and discussions. Experiments show that the proposed approach is feasible for reporting the image quality.

Keywords: Image restoration, Image quality, Activity region, Quadtree

I. INTRODUCTION

Image quality is often concerned in many fields of image processing. For example, the ultimate goal of image enhancement and restoration techniques is to improve an image in some sense (Sezan and Tekalp, 1990; Reeves and Mersereau, 1990; Kang and Katsaggelos, 1995). Enhancement techniques basically are usually heuristic procedures designed to manipulate an image in order to take advantage of the psychophysical aspects of the human visual system. By contrast, restoration techniques are oriented toward modeling the degradation and applying the inverse process in order to recover the original image that has been degraded by using some a priori knowledge of the degradation phenomenon (Sezan and Tekalp, 1990; Lagendijk et al, 1990). Such an approach usually involves formulating a criterion of goodness that will yield some optimal estimation of the desired result. In addition, in image compression, the removal of psychovisually redundant data results in a loss of real or quantitative visual information (Chen et al, 1994). Because information of interest may be lost, a repeatable or reproducible means of quantifying the nature and extent of information loss is highly desirable. Two general classes of criteria are used as the basis for such an assessment: (1) objective fidelity criteria and (2) subjective fidelity criteria. The related objective fidelity criteria are mean-square signal-to-noise ratio, root-mean-square error, and mean-absolute error between the input image and the output image. Although objective fidelity criteria
offer a simple and convenient mechanism for evaluating information loss, most *enhanced, restored,* or *decompressed* images ultimately are viewed by human beings. Accordingly, a suggestion was made that measuring image quality by the subjective evaluations of a human observer is often more appropriate (Gonzalez and Woods, 1992; Cornsweet, 1970).

In addition to the above known properties for image quality, the following questions may also be relevant. Why do we want to perform image enhancement or restoration upon a given image? Aside from the subjective evaluations of a human observer, what can tell us the image quality is good or needs to be processed? If the image quality is good, why do we need to restore such an image? If there is not any reference image, how can we measure the image quality related to itself? In addition, why is measuring image quality by the subjective evaluations of a human observer more appropriate? Our goal in developing an effective algorithm in computer vision is to answer these questions.

In fact, the currently used objective fidelity criteria cannot solve the detail variations of an image since they are usually computed with a mean operator applied to the whole image. Useful variations will be suppressed so that the computed value cannot represent image quality such as when judged by human observation. By contrast, although there exist some differences in subjective evaluations by different human observers, the ratings are always more acceptable. This is due to the *cumulative noticeable information* selected by the attention mechanism in human visual perception (Morgan and King, 1966). Based on this knowledge, in this paper, we present an effective algorithm to measure the image quality by comparison to itself, which can represent not only objective but also subjective fidelity quality. A set of 24 gray images (Image (1) ~ Image (24)) with 256 × 256 pixels shown in Fig. 1 will be used for experiments and discussions.

II. THE PROPOSED APPROACH

Since the cumulative noticeable information selected by the attention mechanism in human visual perception is of great importance, the activity regions of an image may be first located. Then a score for each activity region is computed to reflect the noticeable information of this region. Before constructing the cumulative noticeable information, the histogram of the scores for all activity regions should be found. Finally, a score will
be computed based on the cumulative noticeable information. This score can represent the objective fidelity quality, and its corresponding assigned-rate may also represent the subjective evaluation for the image quality.

1. Activity regions

The noticeable information in human vision can be regarded as an activity region in a given image. An activity region has a higher spatial frequency. Thus, to locate the activity regions, in this paper, a split-and-merge algorithm using $q$-level quadtree structure (Pavlidis, 1982) based on an activity test is applied on a $2^N \times 2^N$ gray image. A region is called active if

$$\sigma_i \geq T$$

where $\sigma_i$ denotes the standard deviation of the $i$th activity region; $T$ is a threshold. To facilitate the presentation of our approach, the split-and-merge using a quad tree (Pavlidis, 1982) is briefly introduced in the following.

Let the image size be $2^N \times 2^N$. The basic traversal procedure starts at level $q$, which contains $4^q$ squares of size $2^{N-q} \times 2^{N-q}$ each. Thus, the whole image corresponds to level 0, and single pixels correspond to level $N$. Let the $x - y$ coordinates of the top left corner of the whole image be $(0,0)$, and let index $i_4$ be used for the traversal of the linked list expressed in base 4 so that the $x - y$ coordinates of the top left corner of the square can be found immediately. If $d_0, d_1, ..., d_k, ...$, are the digits of $i_4$ starting from the least significant, then each $x - y$ coordinate of the square can be found by the following equations:

$$x = \sum_{k=0}^{q-1} (d_k \mod 2) \cdot 2^{N-q+k},$$

$$y = \sum_{k=0}^{q-1} \left\lfloor \frac{d_k}{2} \right\rfloor \cdot 2^{N-q+k},$$

The symbol $\lfloor a \rfloor$ denotes the greatest integer less than or equal to $a$. The range of the coordinates is from 0 to $N-1$. Considering the tradeoff between noticeable information extraction and computation cost, a reasonable block size is $4 \times 4$. If the input image is $256 \times 256$, then $q = 6$.

To merge the similar neighboring regions, the following criteria are adopted. Let $\sigma_1$, $\sigma_2$, $\sigma_3$, and $\sigma_4$ be the standard deviations for the four squares of a splitting region whose
standard deviation is denoted by $\sigma_5$. If

$$\sigma_i \geq T, \ and \ \sigma_5 \geq \sigma_i, \ \forall i,$$

then the four squares are merged, and the standard deviation of the merging block is changed to $\sigma_5$. In our current system, the threshold $T$ is selected experimentally to be 10 and illustrated in Fig. 2. Figure 2(a) shows the well-known MOON image. When $T = 5$, there are too many blocks (2654 blocks) to be labeled. That is, many blur or uniform blocks which are not activity regions are labeled. When $T = 15$, the labeled blocks (418 blocks) are reduced, and some noticeable regions are lost. When $T = 10$, the labeled blocks (919 blocks) are suitable by our visual inspection as shown in Fig. 2(b). After our experiments for examining the $T$ value, $T = 10$ is used in our current approach. As a result, the chosen threshold and the standard deviation of an activity region are useful to reflect the noticeable information for an activity region.

2. Score computation of an activity region

In our approach, the activity regions regarded as the raw data are adopted for measuring the image quality. Since the standard deviation $\sigma_i$ for the $i$th activity region is greater than threshold $T$, the more the difference $\sigma_i - T$, the stronger is the noticeable information for this activity region. Hence, we can use $\sigma_i - T$ quantized with an interval $\delta$ to score the $i$th activity region, denoted by $score_i$. Let the $score_i$ be ranged in $[1, 100]$, then the $score_i$ may be expressed by

$$score_i = \min \left(\left\lfloor \frac{\sigma_i - T}{\delta} \right\rfloor + 1, 100 \right).$$

From the statistics of our experiments for all activity regions, $\delta = 0.6$ is suitable for ranging the score of an activity region from 1 to 100.

3. Statistics of computed scores

The statistics used for the computed scores of all activity regions are histogram and its cumulative density function (cdf). Scores similar to these two statistics have been successfully applied to the visual evaluation for a compressed image (Pavlidis, 1982). Since the histogram of a score $i$ reflects the number of activity regions with respect to that score, its corresponding cumulative histogram $cdf_i$ denotes the number of activity
regions with scores \( \leq i \) (Note that all the histograms and cumulative density functions are normalized in the range \([0.0, 1.0]\) in our experiments). From the statistical viewpoint, a histogram skewed toward the lower scores represents most regions having lower activity. Such an image can be rated as more blur. Whereas a histogram skewed toward the higher scores represents most regions having higher activity. Such an image can be rated as more clean. These important observations can be readily transformed into the cumulative density function to provide the so-called cumulative noticeable information. That is, for an image with more blur, its \( cdf \)’s shape denotes a higher speed to reach the maximum of the \( cdf \); whereas for a more clear image, its \( cdf \)’s shape denotes a lower speed to reach the maximum of the \( cdf \), respectively.

Figure 2(c) and 2(d) show the histogram and its cumulative distribution, respectively, for the activity regions shown in Fig. 2(b). In accordance with the previous discussion, Image (11) is a blur-oriented image. Figure 3 shows the corresponding results for Image (15), which is a clean-oriented image. Furthermore, Figure 4 shows the corresponding results for Image (24), which is also a blur-oriented image. The histograms and cumulative distributions for these images show that they match the proposed idea.

4. Objective and subjective evaluations

Since the \( cdf \) of the scores of activity regions for an image provides the cumulative noticeable information, an objective evaluation can be easily constructed based on the \( cdf \). Since the \( cdf \) has been normalized to the range \([0.0, 1.0]\), if we want to display the score of an image quality in the range \([1, 100]\), an objective total score for measuring the image quality may be reached by

\[
total\_score = \sum_{i=1}^{100} \left[ 1 - (cdf_i)^3 \right],
\]

where \( i (= 1 \sim 100) \) is the score of an activity region according to Eq. (5). The less the total score, the more blurred the image quality, and vice versa. For example, the total scores (as an objective evaluation) for Images (11), (15), and (24) are 23.25, 74.03, and 25.41, respectively.

Besides the objective evaluations, side-by-side comparisons may be done with a grade such as \( \{1, 2, 3, 4, 5\} \) to represent the subjective evaluations \{more blur, blur, passable, clear, more clear\}, respectively. The relationship between total score (for objective
evaluation) and grade (for subjective evaluation) may be defined by

\[
\text{grade} = \begin{cases} 
1, & \text{if } \text{total\_score} \leq \theta_1, \\
2, & \text{if } \theta_1 < \text{total\_score} \leq \theta_2, \\
3, & \text{if } \theta_2 < \text{total\_score} \leq \theta_3, \\
4, & \text{if } \theta_3 < \text{total\_score} \leq \theta_4, \\
5, & \text{otherwise.} 
\end{cases} 
\tag{7}
\]

To decide the \( \theta \)s, a set of 504 images have been sorted by visual inspection into the five grades. Their relationships between total score (objective evaluation) and grade (subjective evaluation) are shown in Fig. 5. The found gaps are regarded as our \( \theta \)s, that is, \( \theta_1 = 30, \theta_2 = 43, \theta_3 = 57, \) and \( \theta_4 = 70 \). For example, the subjective evaluations for Images (11), (15) and Image (24) are “grade = 1 representing a more blurred quality,” “grade = 5 representing a more clear quality,” and “grade = 1 representing a more blurred quality,” respectively.

After applying the proposed approach to all the images shown in Fig. 1, Figure 6 again shows the original images in descending order (from the more clear quality to the more blurred quality) according to their total scores obtained by Eq. (6). Comparing all the grades in descending order to the corresponding image, the results are very close to our visual inspection grades for these images.

III. RESULTS AND DISCUSSIONS

The proposed approach was implemented in MATLAB (version 4.0), run on a Pentium-based personal computer with Windows 95. A set of 24 gray images (Image (1) ~ Image (24)) with 256 \( \times \) 256 pixels shown in Fig. 1 were used for experiments and discussions. Besides Fig. 6, four other transformed versions of the original images were further tested to confirm our approach. They are (1) the versions blurred by uniform linear motion, (2) versions blurred by Gaussian filtering, (3) versions sharpened by high-boost spatial filtering, and (4) versions sample-reduced by reducing spatial resolution, respectively. The first three types of transformed versions can be obtained by

\[
g = h * f, 
\tag{8}
\]

where \( f \) and \( g \) are the original image and the transformed one, respectively; and \(*\) denotes the spatial convolution. All the transform algorithms are also implemented in
MATLAB.

1. Images blurred by uniform linear motion

The linear motion blur operator over $L$ pixels under an angle of $\phi$ is defined as (Lagendijk et al, 1990):

$$h(x, y; L, \phi) = \begin{cases} \frac{1}{C}, & \text{if } \sqrt{x^2 + y^2} \leq \frac{L}{2} \text{ and } \frac{x}{y} = \tan \phi, \\ 0, & \text{elsewhere}, \end{cases}$$

(9)

where $\sum_{x,y \in M} h(x, y) = 1.0$, $L$ is the motion amount in pixels, $M$ is a defined $L \times L$ mask, $\phi$ is the angle of motion direction corresponding to the horizontal axis, and $C$ is constant, respectively. With the linear motion blur operator, the blurred version $g$ may be obtained by using Eq. (8). Figure 7 shows Image (15) results blurred by uniform linear motion ($L = 11$, $\phi = 0$). Comparing the results of Fig. 7 with those of Fig. 3, the histogram and cumulative distribution of activity regions show obviously that the image has been changed from a *more clear* quality (total score = 74.03, grade = 5) to a *blur* quality (total score = 32.47, grade = 2).

2. Images blurred by Gaussian filtering

The Gaussian out-of-focus blur operator may be defined as (Lagendijk et al, 1990):

$$h(x, y; W, \sigma) = C \exp \left\{ -\frac{x^2 + y^2}{2\sigma^2} \right\},$$

(10)

where $\sum_{x,y \in M} h(x, y) = 1.0$, $M$ is a defined $W \times W$ mask, $\sigma$ denotes the standard deviation, and $C$ is constant, respectively. With the Gaussian out-of-focus blur operator, the blurred version $g$ may be obtained by using Eq. (8). Figure 8 shows Image (15) results blurred by Gaussian filtering ($\sigma = 1.8$, $W = 7$). Comparing the results of Fig. 8 with those of Fig. 3, the histogram and cumulative distribution of activity regions show obviously that the image has been changed from a *more clear* quality (total score = 74.03, grade = 5) to a *blur* quality (total score = 31.74, grade = 2).

3. Images sharpened by high-boost spatial filtering

Because the high-boost filtering method can produce an image that looks more like the original image with a relative degree of edge enhancement that depends on a parameter of $A$ (Gonzalez and Woods, 1992), we apply it to all original images for producing
sharpened images such that we can examine their relative measuring results. The high-
boost spatial filtering operator is defined as:

\[ h = \frac{1}{g} \times \begin{bmatrix} -1 & -1 & -1 \\ -1 & w & -1 \\ -1 & -1 & -1 \end{bmatrix}, \quad w = 9A - 1, \quad A \geq 1. \] (11)

The sharpened image is obtained by the following process:

\[ g = h * f + f. \] (12)

Figure 9 shows Image (15) results sharpened by the high-boost filtering \((A = 1.3)\). Comparing the results of Fig. 9 with those of Fig. 3, the histogram and cumulative distribution of activity regions show obviously that the image has been changed from a total score = 74.03 to the total score = 95.53. According to our grade assignment in Eq. (7), the transformed image is also a **more clear** quality (grade = 5).

### 4. Images sample-reduced by reducing spatial resolution

Reducing the spatial resolution of an image may also degrade the image quality. To confirm our method can also measure such a sample-reduced image, we preserve the image scale 256×256 pixels and resample the original image at 128×128 resolution. That is, the mean value of four gray values of the 2×2 pixels is used to replace their originals. Figure 10 shows Image (15) results sample-reduced by reducing spatial resolution to \((128 \times 128)\). Comparing the results of Fig. 10 with those of Fig. 3, the histogram and cumulative distribution of activity regions show obviously that the image has been changed from a **more clear** quality (total score = 74.03, grade = 5) to a **passable** quality (total score = 55.98, grade = 3).

### 5. Discussions

Figure 11 shows four performance comparisons between original images and the transformed versions with some different parameters. For uniform linear motion blur, the results with parameters \(\phi = 0\), and \(L = 3, 5, 7, 9, 11, 13, 15\) are reported in Fig. 11(a). For Gaussian out-of-focus blur, the results with parameters \(W = 7, \sigma = 0.3, 0.6, 0.9, 1.2, 1.5, 1.8\) are reported in Fig. 11(b). For high-boost sharpening, the results with parameters \(A = 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6\) are reported in Fig. 11(c). The results of reducing
spatial resolution are reported in Fig. 11(d). Based on the comparisons, we have the following observations:

1. For images blurred by using uniform linear motion, the larger the parameter \( L \) (representing more blur), the lower the total score by Eq. (6). See Fig. 11(a) for reference.

2. For images blurred by Gaussian filtering, the larger the parameter \( \sigma \) (representing more blur), the lower the total score by Eq. (6). See Fig. 11(b) for reference.

3. For images sharpened by high-boost spatial filtering, in general, the larger the parameter \( A \) (representing more clear), the higher the total score by Eq. (6). See Fig. 11(c) for reference. However, the results for Images (5), (6), (16), and (20) have an unusual phenomenon. This is because some original blur regions enhanced by the process result in the increase of the number of activity regions, but the lower score by Eq. (5) for the increased activity region may yield a lower total score by Eq. (6).

4. For images sample-reduced by reducing spatial resolution, the image quality becomes more blur due to the blocky effect. See Fig. 11(d) for reference.

5. Cartoon images have a higher total score due to the simple colors of foreground and background always producing a very clean edge between any two regions. Whereas human face images have a lower total score due to the real colors always producing a local smooth variation even at the edge portion from the micro-view point.

6. From each measured image, the activity regions may be exactly obtained by our approach, and their scores may also reflect the amount of activity for a region.

A special case of higher image scores may be investigated by adding a random noise into an original image as illustrated in Fig. 12. Images (1), (12), (4), and (7) with ascending order and the addition of 30\%, 50\%, 70\% random noise are used in this experiment. The comparison shows that the higher the degree of random noise added, the higher the image score is. Because the random noise appears rarely in modern commercial systems, such a special case is ignored in our current approach. Another special case may also be of interest, that is, what is the image score for enlarging an
original image? To investigate this case, Images (1), (12), (4), and (7) are scaled up by factors of 2 and 4, respectively, whose computed scores are listed in Table 1 ($q = 6$). According to this result, we find that the variation of image scores for an enlarged version corresponding to its original one is very small since the image information for an enlarged version is not reduced usually.

Based on the experiments and discussions mentioned above, our proposed approach can effectively perform not only objective evaluation by scores but also subjective evaluations by grades for measuring image quality.

IV. CONCLUSIONS

An approach to measuring image quality is presented in this paper. Based on the cumulative noticeable information selected by the attention mechanism in human visual perception, in our approach, the activity regions of an image are first located. Then a score for each activity region is computed to reflect the noticeable information in this region. The histogram of the scores for all activity regions is found to construct the cumulative noticeable information. A total score is finally computed based on the cumulative noticeable information to represent objective fidelity quality, and its corresponding assigned-rate is to represent subjective evaluation for the image quality. For a gray image, the approach can provide both objective evaluation and subjective evaluation for representing the image quality, which may be applied to (1) the question of whether to continue processing, (2) image-based auto-focusing in computer vision, (3) measurement of image visibility, etc. The type identification and parameter estimation of a blurred image (for example, estimating the motion parameters for a linear motion blurred image (Chen and Choa, 2000)) will be the subject of further work.

ACKNOWLEDGMENTS

This work was partially supported by National Science Council of Republic of China under grant NSC 87-2213-E-155-020.
References


Fig. 1. Original images.
Fig. 2  (a) Original MOON Image (11).  (b) Labeled blocks (called activity regions) with $T = 10$.  (c) Histogram.  (d) Cumulative distribution.  Where $N = 8$ and $q = 6$. 
Fig. 3 (a) Original image of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. 

Where $N = 8$ and $q = 6$. 


Fig. 4 (a) Original image of Image (24). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. 
Fig. 5  Relationship between total score (objective evaluation) and grade (subjective evaluation) obtained with 504 observations. Here we have $\theta_1 = 30$, $\theta_2 = 43$, $\theta_3 = 57$, and $\theta_4 = 70$, respectively.
Fig. 6 Original images are reshown in descending sequence of computing scores by the proposed approach.
Fig. 7 (a) Linear motion blur version \((L = 11, \phi = 0)\) of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where \(N = 8\) and \(q = 6\).
Fig. 8  (a) Gaussian blur version ($\sigma = 1.8$, $W = 7$) of Image (15).  (b) Activity regions.  (c) Histogram.  (d) Cumulative distribution.  Where $N = 8$ and $q = 6$.  

19
Fig. 9 (a) Sharpened version ($A = 1.3$) of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. 
Fig. 10  (a) Sample-reduced version (128×128) of Image (15). (b) Activity regions. (c) Histogram. (d) Cumulative distribution. Where $N = 8$ and $q = 6$. 
Fig. 11 Performance comparisons, where abscissa and ordinate represent the image number (from 1 to 24) and the corresponding image score, respectively. (a) Original images vs. the linear motion blur versions. (b) Original images vs. the Gaussian blur versions. (c) Original images vs. the sharpening versions. (d) Original images vs. the sample-reduced versions.
(b)

Fig. 11  (Continued.)
Fig. 11 (Continued.)
Fig. 11 (Continued.)
Fig. 12 Illustration of image scores affected by adding a random noise. This comparison shows that the higher the degree of random noise added, the higher the image score is.

Table 1 Illustration of image scores from enlarging the images.

<table>
<thead>
<tr>
<th>Scaling factor (image size)</th>
<th>Image (1)</th>
<th>Image (12)</th>
<th>Image (4)</th>
<th>Image (7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (256×256), N=8, q=6</td>
<td>47.75</td>
<td>53.96</td>
<td>58.85</td>
<td>61.36</td>
</tr>
<tr>
<td>2 (512×512), N=9, q=6</td>
<td>47.06</td>
<td>53.60</td>
<td>57.98</td>
<td>60.61</td>
</tr>
<tr>
<td>4 (1024×1024), N=10, q=6</td>
<td>46.90</td>
<td>53.77</td>
<td>57.75</td>
<td>60.50</td>
</tr>
</tbody>
</table>