Quantizer design for multilevel BTC

Abstract. In this paper a novel image compression method based on Block Truncation Coding technique is presented. The essence of this method is the designing of both, fixed and adaptive, multilevel quantizers and their appliance for discrete input. Experimentally obtained results show that usage of compression based on this method provide lower bit rate values comparing to the previously BTC-based results, while attaining requested level of quality.

Streszczenie. Zaproponowano nową metodę kompresji obrazu bazującą na technice BTC. Idea tej metody jest zaprojektowanie wielopoziomowych kwantyzatorów stałych i adaptacyjnych. Eksperymenty potwierdzają, że uzyskano lepszą przepływność bez pogorszenia jakości. (Projekt wielopoziomowego kwantyzera do kompresji obrazu)

Keywords: image compression, block truncation coding, multilevel BTC

Stwóra kluczowe: kompresja obrazu, metoda BTC.

Introduction

The amount of data used to represent image is reduced to meet a bit rate requirement, while the quality of the reconstructed image satisfies a requirement for a certain application in a process called image compression. The complexity of computation involved can be applied for desired application properties.

The required quality of the reconstructed image and video is application dependent. In medical diagnosis and television (TV), a certain amount of information loss is allowed. This type of compression is called lossy compression. In application, such as motion picture and video, this type of compression is referred to as lossless compression. In some scientific measurements, we may need the information to meet a bit rate requirement, while the quality of the reconstructed image satisfies a requirement for a certain application properties.

The advantage of this method is transmission of just two values. The represents of these sets are AMBTC [8] method have lower level of complexity and practical realization.

First, related works on multilevel BTC are presented. After that, multilevel fixed quantizer appliance and its adaptation are presented. Obtained experimental results are then discussed. Finally conclusions are derived.

Related works on multilevel BTC

With AMBTC, mean and the first absolute moment \(\alpha\) of \(n x n\) block are preserved. The first absolute moment is defined as:

\[
\alpha = \frac{1}{m} \sum_{i=1}^{m} |x_i - \bar{x}|
\]

The reconstruction levels that preserve \(\bar{x}\) and \(\alpha\) are therefore:

\[
a = \bar{x} - \frac{m \alpha}{2(m - q)}
\]

\[
b = \bar{x} + \frac{m \alpha}{2q}
\]

Donson i DeWitte [10] used 2-level AMBTC output in order to define two thresholds for 3-level BTC. First, each block is quantized with respect to 2-level AMBTC algorithm. Then two thresholds \(t_1\) and \(t_2\) are defined as:

\[
t_1 = (3b_2 + a_2)/4
\]

\[
t_2 = (3a_2 + b_2)/4
\]

with \(a_2\) and \(b_2\) being the outputs of 2-level AMBTC (6) and (7). Finaly representation levels are given with \(a_3\), \((a_3 + b_3)/2\), \(b_3\) where

\[
a_3 = \text{mean of pixels } \leq t_2
\]

\[
b_3 = \text{mean of pixels } > t_1
\]

The advantage of this method is transmission of just two \((a_3\mbox{ and } b_3)\) of three levels.

In paper [11] genetic algorithm is applied over previously mentioned 3-level BTC. Also an optimal threshold determining procedure for obtaining minimal absolute error value is presented. Considering this fact, the following measurement is defined:

\[
MAE = \sum_{i=1}^{m} |x_i - a| + \sum_{i=m-q}^{m} |x_i - b|
\]
However this procedure requires huge amount of calculation so the practical implementation of it for multilevel BTC is limited up to level four. In order to overcome this level number limitation, novel multi-level quantizer is proposed.

**Applying of multilevel quantizer and its adaptation**

The key item in our method is quantizer designing for discrete input [9]. Input samples of the quantizer Q can take \( N_0 \) discrete values, denoted with \( X = \{ x_1, \ldots, x_{N_0} \} \). Probabilities of the discrete levels from the set \( X \) are

\[
P(x_i) = p(x_i) \Delta = \frac{1}{2^s} \exp \left( - \frac{\sqrt{s} x_i}{\sigma} \right) \Delta_x, \quad i = 2, \ldots, N_0 - 1
\]

and

\[
P(x_{N_0}) = p(x_{N_0}) \Delta = \frac{1}{2} \exp \left( - \frac{\sqrt{s} x_{N_0}}{\sigma} \right),
\]

Output levels of the quantizer \( Q \) are denoted with \( y_j, j = 1, \ldots, N \). It is valid that \( N_0 = N \), where \( L \) is an integer. This means that \( L \) discrete input levels \( X = \{ x_1, \ldots, x_L \} \) are mapped to one output level \( y_j, j = 1, \ldots, N \).

Two quantizers \( Q_1 \) and \( Q_2 \) will be used. \( Q_1 \) is uniform quantizer with \( N_1 \) levels, while the maximal input amplitude is determined by the threshold \( T \). Second quantizer \( Q_2 \) represents the union of two uniform quantizers, where their border line is determined by the threshold \( T \). The first part of second quantizer has codebook size of \( N_1 \) levels while second part \( N_2 \).

The algorithm is performed from left to right and from top to bottom. The proposed algorithm has the following steps:

1. The image is divided into a set of non-overlapping \( M \times M \) blocks (macroblocks).
2. The mean value of pixels in each macroblock \( x_{\text{macro}} \) is calculated, quantized \( \hat{x}_{\text{macro}} \) and transmitted to the receiver.
3. The macroblock \( M_{\text{avg}} \) is divided into a set of non-overlapping \( m \times m \) blocks \( M_{\text{avg}} = \bigcup_{s=1}^{s=1} M_{\text{avg}} \) (microblocks) where \( s \) is the total number of microblocks within macroblock \( s = \frac{M \times M}{m \times m} \). The mean value of pixels in the microblock \( x_{\text{micro}} \) is calculated. Then, the difference between the mean value in the microblock and the quantized mean value of the macroblock is calculated,

\[
x_{\text{diff}} = x_{\text{micro}} - \hat{x}_{\text{macro}}.
\]

After that, this difference is quantized \( \hat{x}_{\text{diff}} \) and transmitted to the receiver.
4. The pixel values in each individual microblock are substituted with \( x_{\text{diff}} \), which is the difference between the pixel value \( x \) and the mean value of the microblock available in the receiver (i.e. in the decoder): \( x_{\text{micro}}^* = \hat{x}_{\text{macro}} + \hat{x}_{\text{diff}} \). Therefore, we have that

\[
x_{\text{diff}} = x - (x_{\text{micro}}^*) = x - (\hat{x}_{\text{macro}} + \hat{x}_{\text{diff}})
\]

5. If the relation \( |x_{\text{diff}}| \leq T \) is valid for each pixel values from microblock then indicator bit “1” is assigned. Quantization of \( x_{\text{diff}} \) is done using quantizer \( Q \) and quantized values \( \hat{x}_{\text{diff}} \) are transmitted to the receiver. Then step 7 is performed. If, for at least one from microblock values, the relation is not valid then step 6 is performed.
6. Indicator bit “0” is assigned. The relation \( |x_{\text{diff}}| > T \) is questioned for each pixel values from microblock. If the condition is satisfied, then in corresponding bit plane “ indicator bit “1” is assigned and quantization is performed by the first part of quantizer \( Q_1 \). On counter indicator bit “0” is assigned and quantization is performed by the second part of quantizer \( Q_2 \). Quantized values \( \hat{x}_{\text{diff}} \) are transmitted to the receiver.
7. Go to the step 3 until all macroblocks are processed.
8. Go to the step 2 until all macroblocks are processed.

In the previous algorithm, with \( * \) are denoted quantized values and with \( \hat{\cdot} \) are denoted values available to decoder.

To summarize: \( \hat{x}_{\text{macro}}, \hat{x}_{\text{diff}} \) and \( \hat{x}_{\text{diff}} \) are transmitted to the receiver and these values are available to the decoder. Reconstructed pixel value on the output of the decoder is

\[
x^* = \hat{x}_{\text{macro}} + \hat{x}_{\text{diff}} + \hat{x}_{\text{diff}}.
\]

In (13) the first step, \( \hat{x}_{\text{macro}} \) is used instead of \( x_{\text{macro}}^* \) since \( \hat{x}_{\text{macro}} \) is available to decoder. In (14) the step 4, \( \hat{x}_{\text{micro}}^* \) is used instead of \( x_{\text{micro}}^* \) since \( \hat{x}_{\text{micro}}^* \) is available to decoder. Therefore, in the coding process we use values which will be available to decoder, to minimize the reconstruction error (i.e. the difference between the original and the reconstructed images).

We introduced the following parameters: \( r_{\text{macro}}, r_{\text{av}} \) and \( r_{\text{diff}} \) denote the number of bits that is used for transmission of \( \hat{x}_{\text{macro}}, \hat{x}_{\text{diff}} \) and \( \hat{x}_{\text{diff}} \) respectively. \( N_{\text{macro}}, N_{\text{micro}} \) and \( N_{\text{pixels}} \) denote the total numbers of macroblocks, microblocks and pixels, respectively. The average bit rate per pixel \( R_{\text{av}} \) for fixed quantizer can be calculated according to the relation:

\[
R_{\text{av}} = \frac{N_{\text{macro}} r_{\text{macro}} + N_{\text{micro}} r_{\text{av}} + r_{\text{diff}}}{N_{\text{pixel}}
\]

where:

\[
r_{\text{diff}} = \begin{cases} 2 & \text{if } (\forall x_{\text{diff}} \in M_{\text{avg}}) \Rightarrow |x_{\text{diff}}| \leq T_h \\ 1 + r_1 & \text{if } (\exists x_{\text{diff}} \in M_{\text{avg}}) \Rightarrow |x_{\text{diff}}| > T_h \\ \end{cases}
\]

for \( i = 1, \ldots, m \times m \) and where:

\[
r_1 = \begin{cases} 2 & |x_{\text{diff}}| \leq T_h \\ 5 & |x_{\text{diff}}| > T_h \\ \end{cases}
\]

The maximal amplitude of the adaptive quantizer depends on the quantized standard deviation of the microblock \( \sigma \), i.e. \( \sigma_{\text{adapt}} = k \sigma \), where \( k \) is a parameter of proportionality [9].

Step 4 of previously described algorithm, is extended with new step 4.1.

4.1. The standard deviation \( \sigma \) of such obtained values \( x_{\text{diff}} \) for the microblock is calculated. After that, this standard deviation is quantized (\( \hat{\sigma} \)) and transmitted to the receiver.

\( r_\sigma \) denotes the number of bits used for transmission of \( \hat{\sigma} ). R_{\text{av}} \) for adaptive quantizer can be calculated according to the relation:

\[
R_{\text{av}} = \frac{N_{\text{macro}}^* r_{\text{macro}} + N_{\text{micro}}^* r_{\text{av}} + r_{\text{diff}}}{N_{\text{pixel}}}
\]

where conditions (17) and (18) are still valid.

Based on quantized standard deviation \( \hat{\sigma} \) quantizers \( Q_1 \) and \( Q_2 \) are adopted in step 5 and 6.

**Experimental results**

The quality of the reconstructed image is measured with PSNR (peak signal-to-quantization-noise ratio), which is defined as followed:

\[
\text{PSNR} = 10 \log_{10} \left( \frac{M \times M}{\text{mean}^2(x_{\text{diff}}^2)} \right)
\]
(20) \[ PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right) \] [dB]

(for grayscale images \( x_{\text{max}} = 255 \) and \( MSE = \sum (x - \hat{x})^2 \) is the mean square error between the original and the reconstructed images, where summation is done for all pixels in the image.

In this section we present experimental results, obtained by applying algorithm from previous section on three grayscale images (Lena, Airplane and Peppers), shown in Fig. 1. These images are 512x512 of pixel size and each pixel can take integer values from 0 to 255.

Based on few decisions, threshold \( T_h \) value is set on 15 (\( r_{\text{macro}} = 6 \) bits and \( r_{\text{micro}} = 5 \) bits). In Table 2 results obtained for the proposed multilevel BTC with fixed quantizers \( Q_1 \) and \( Q_2 \) appliance are given.

Table 2. Results obtained by applying new multilevel BTC with fixed quantizers

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lena</td>
<td>42</td>
<td>3.042</td>
</tr>
<tr>
<td>Airplane</td>
<td>42.11</td>
<td>3.11</td>
</tr>
<tr>
<td>Peppers</td>
<td>41.27</td>
<td>3.057</td>
</tr>
</tbody>
</table>

Performances of newly proposed method with adaptive quantizers \( Q_1 \) and \( Q_2 \) appliance are presented in Table 3. Presented results are compared with GA over 4-level BTC. It should be mentioned that the 4-level BTC rate for all images is \( R = 3.5 \).

Table 3. Results obtained by applying new multilevel BTC with adaptive quantizers

<table>
<thead>
<tr>
<th>Image</th>
<th>new multilevel BTC</th>
<th>multilevel BTC with GA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>R</td>
</tr>
<tr>
<td>Lena</td>
<td>43.95</td>
<td>3.23</td>
</tr>
<tr>
<td>Airplane</td>
<td>44.83</td>
<td>3.3</td>
</tr>
<tr>
<td>Peppers</td>
<td>43.24</td>
<td>3.24</td>
</tr>
</tbody>
</table>

Conclusion

By applying newly proposed multilevel quantizer model for discrete input, \( PSNR \) measurement of quality, has overachieved quality of multilevel BTC with GA for almost 4 dB. Comparing with multilevel BTC with GA transmission, we derive conclusion that not only we have achieved better quality, but also we can reach better compression for 0.25 bit. The main benefit of our algorithm is that we have reached this quality without using GA, so the practical implementation of our model is less complex, and is not limited up to given level number.

Fig.1. The grayscale images, size 512x512 pixels, a) Lena, b) Airplane, c) Pepper

REFERENCES


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