Abstract

In JPEG-LS, simple edge detection techniques are used in determining the predictive value of each pixel. These techniques only detect horizontal/vertical edges and have only been optimized for the prediction of pixels in the locality of such edges. Thus, JPEG-LS produces large prediction errors in the locality of diagonal edges. We propose a low complexity technique that accurately detects diagonal edges and efficiently predicts pixels, based on the information available within the standard predictive template of JPEG-LS. We show that the proposed technique outperforms JPEG-LS in terms of predicted mean squared error, by margins of up to 15%.

Keywords: JPEG-LS; Lossless image coding; Predictive coding; Edge detection

1. Introduction

High quality, high compression rates and low computational cost are important factors in many areas of digital imaging, ranging from digital photography to advanced consumer electronic applications. However, the relative importance of these factors is application dependant. For example, in video telephony applications, low computational cost and high compression rates are imperative, whereas in medical imaging devices, high quality and low computational cost are a priority [13,15]. Due to the high demand of applications that require coding schemes that satisfy the latter set of conditions, lossless/near-lossless compression schemes [1–12] such as DPCM [16], FELICS [5], LOCO-I [2] have by now evolved into an international standard, JPEG-LS [1], with the major contribution coming from LOCO-I (Low Complexity, Context-based Lossless Image compression algorithm).

LOCO-I, the compression algorithm that mostly contributed to the JPEG-LS standard, follows a traditional coding structure, namely, predictor–modeler–coder. In the context modelling section of the JPEG-LS algorithm, only horizontal and vertical edges, in the vicinity of a pixel to be predicted $x_i$, are considered in the determination of its context. Unfortunately, this means that in the presence of a diagonal edge, its erroneous detection as a horizontal or a vertical edge would result in a wrong context classification for the pixel $x_i$. This would result in a higher prediction error, $e_i$, and an ultimate reduction of the rate-distortion performance of the JPEG-LS algorithm.

Even though one could argue that the likelihood of a diagonal edge is minimal as compared to a horizontal or a vertical edge and that the errors resulting from the wrong context classifications could be neglected in exchange of a lower complexity context modelling and prediction approach, existing research [14] indicates that this is not always the case. It has been shown that, by considering the relative gradients present within the so-called predictive template of JPEG-LS (Fig. 1) it is possible to detect these diagonal edges establish ways to accurately predict pixels in the vicinity of such edges. In Ref. [14] Jiang et al. proposed a method that is based on six thresholds to detect diagonal edges and perform accurate prediction. However, the use of a large number of thresholds in context determination increases the complexity of the approach and also makes it rather difficult to determine the best set of six parameters that could be applied for the efficient coding of a wider range of images. In addition to this, experiments carried out by us showed that certain constraints that have been used in this work are ‘too tight’ and would result in the elimination of certain diagonal edges from the selection process. In particular, it is in fact possible to more accurately predict...
near single pixel width diagonals. In order to solve the above issues we propose a low complexity approach that is based only on two, easily deterministic thresholds (parameters). The flexibility/simplicity and the increased accuracy of the proposed algorithm in the context determination process and in prediction, is shown to clearly outperform the proposed algorithm in the context determination process only on two, easily deterministic thresholds (parameters).

For clarity of presentation, this paper is divided into five main sections. Apart from Section 1, which is an introduction to the research context discussed in this paper, Section 2 introduces the reader to the details of the prediction scheme used by JPEG-LS/NLS standard and identifies associated problems using well-supported examples. Section 3 describes the proposed solution, which is based on the accurate detection of diagonal edges and accurate prediction of pixels in the vicinity of such edges. Section 4 provides the experimental results in support of the proposed modification and a detailed analysis of the results. Finally, Section 5 concludes with suggestions for future work and improvements.

2. JPEG-LS context classification and prediction scheme

In the following discussion, we limit our analysis and modifications to the lossless-mode operation of JPEG-LS. However, the ideas presented below could be easily extended to the near-lossless mode of operation.

2.1. Context classification

The context classification process of JPEG-LS is based on the simple causal template depicted in Fig. 1. Here, \( x \) is the pixel to be predicted and \( a, b, c \) and \( d \) are previously encoded pixels in the immediate neighbourhood of \( x \). For the purpose of simplicity, we have ignored the time index \( i \) from the above notation.

According to the JPEG-LS context classification procedure, pixel \( x \) is defined to be in a smooth region if all four neighbouring pixel values, \( a, b, c \) and \( d \) are equal. Under such conditions, run-length coding is applied in encoding the pixel values. If this condition is not satisfied, the context is classified as non-smooth, and simple edge detection based predictive coding is used in coding \( x \).

2.2. Predictive coding

For non-smooth areas, JPEG-LS uses the following simple edge detection/prediction scheme, to determine the predictive value, \( \hat{x} \) of each pixel, \( x \). If \( c \geq \max(a, b) \Rightarrow \hat{x} = \min(a, b) \), else if \( c \leq \min(a, b) \Rightarrow \hat{x} = \max(a, b) \). If \( c \) does not satisfy both conditions stated above, it is predicted as \( \hat{x} = a + b - c \). Further analysis of this edge detection/prediction scheme reveals the following:

- An edge would be detected among the three pixels \( a, b \) and \( c \), when either \( c \geq \max(a, b) \) or \( c \leq \min(a, b) \) is satisfied. When \( c \geq \max(a, b) \), the presence of a horizontal edge is signified by \( \max(a, b) = a \) and the presence of a vertical edge is signified by \( \max(a, b) = b \). Similarly, when \( c \leq \min(a, b) \) the presence of a horizontal edge is signified by \( \min(a, b) = a \) and a vertical edge is signified by \( \min(a, b) = b \).

- When \( \min(a, b) < c < \max(a, b) \), there is not enough justification to determine whether there is an edge or not. However, contrary to the observations in Ref. [14], it is possible to show that the pixel value \( x \) is not essential in the determination of the context. We observe that under this condition, a vertical/horizontal edge may be still detected if the value of \( c \) is sufficiently close enough to either \( \min(a, b) \) or \( \max(a, b) \) and the difference between \( a \) and \( b \) is sufficiently large (this issue is addressed more detailed in Section 3).

In other words, the predictor \( \hat{x} = a + b - c \), used by JPEG-LS under this condition, is very well balanced to accurately predict \( x \), regardless of the fact whether the context is smooth or contains a vertical/horizontal edge. This is easily proved by rearranging the terms of \( \hat{x} = a + b - c \) as follows and by further analyzing the results

\[
\hat{x} - a = b - c
\]

\[
\hat{x} - b = a - c
\]

Both equations above depict pixel gradient equalizations across boundaries (or more precisely, vertical/horizontal edges). When Eq. (1) is satisfied, one could expect a horizontal edge to be present and when Eq. (2) is satisfied one could expect a vertical edge to be present. Both equations support the presence of a smooth area, as such an area could be characterized by small differences between adjacent pixel values, \( a, b \) and \( c \). In other words, if \( a \equiv c \Rightarrow \hat{x} \equiv b \) and if \( b \equiv c \Rightarrow \hat{x} \equiv a \), and either way since \( a \equiv b \), \( \hat{x} \) would be approximately the same. Thus the above, clearly proves the excellent performance of the predictor used by JPEG-LS under the condition \( \min(a, b) < c < \max(a, b) \).
Unfortunately, there is one more type of edge that is possible: i.e. a diagonal edge, which has been ignored by the JPEG-LS algorithm. In support of the idea of disregarding the presence of diagonal edges, one may claim that a combination of many vertical and horizontal edges can produce a line with arbitrary shape or edges in an image. However, what matters here is whether the description by the two edges (horizontal/vertical) would be accurate enough to minimize the predictive errors. In cases where a diagonal edge exists inside the predictive template, it can be expected that the errors produced can be unnecessarily high.

Thus, in order to find a suitable low-cost solution to the above problem, we propose the introduction of simple diagonal edge detection based prediction, for those pixel locations that are in the vicinity of diagonal edges. The presence of three types of edges is expected to increase the prediction accuracy of arbitrary shaped object boundaries/edges, leading to improvements in rate-distortion performance of JPEG-LS image compression standard.

3. Diagonal edge detection and prediction

3.1. Diagonal edges and their detection

Fig. 3(a)–(d) show the four main orientations of diagonal edges that may be considered for further improvement of the JPEG-LS prediction scheme. The highlighted rectangles represent the opposite type (high/low) of pixel intensity to that of the non-highlighted rectangles. A closer investigation of these patterns shows that it is not possible to accurately identify the diagonal edge orientations indicated in Fig. 3(a) and (b), by means of low cost techniques limited to the standard predictive template of JPEG-LS (Fig. 1). The reason for this is that the value of the pixel to be predicted $x$ cannot be involved in the decision making process and due to this fact, it can not be guaranteed whether the edge is actually a diagonal edge or rather a horizontal (Fig. 3(a))/vertical edge (Fig. 3(b)).

However, in the case of orientations shown in Fig. 3(c) and (d), it is possible to accurately establish the presence of a diagonal edge. Fig. 3(c) shows a diagonal edge that separates two areas of differing intensity and Fig. 3(d) shows a diagonal line of single pixel width. A close comparison of the pixel intensities of Fig. 3(c) and (d) indicates that a diagonal edge is characterized by the fact that $a \equiv b$ and pixel $c$ being greatly different from both $a$ and $b$. Interestingly, we find that these conditions would not be worthwhile testing under the condition, $\min(a, b) < c < \max(a, b)$. This is due to the fact that under this condition when $a \equiv b \Rightarrow c \equiv a$ and $c \equiv b$. This actually depicts a smooth texture rather than any kind of edge as discussed previously. Thus our search for diagonal edges should happen when the condition $c \equiv \max(a, b)$ or the condition $c \equiv \min(a, b)$ is satisfied.

By considering the above, we now formulate the formal conditions for the accurate detection of diagonal edges of the nature shown in Fig. 3(c) and (d), as follows:

\[
((c - \max(a, b)) > T_1 \text{ OR } (\min(a, b) - c) > T_1) \text{ AND } (\abs(a - b) \leq T_2)
\]  

(3)
In Eq. (3), OR and AND represent the standard Boolean operations, whereas abs represents the absolute value of the element quoted within parenthesis. \( T_1 \) and \( T_2 \) are predefined positive thresholds (ideally \( T_1 > T_2 \)) that could be used in deciding the contrast of pixel values present across the detected diagonal edges. Further analysis of the above gradients reveal that it is the conditions that are opposite to what has been stated above, that would be satisfied when a horizontal or a vertical edge is present. Thus it provides an accurate means of differentiating diagonal edges from vertical/horizontal edges under the condition \( c \geq \max(a, b) \) or \( c \leq \min(a, b) \).

Accurate detection of diagonal edges only amounts to a more accurate context classification and is not the only factor that results in the ultimate aim of achieving better prediction accuracy. In Section 3.2, we introduce the reader to a modified prediction strategy, which increases accuracy of prediction near diagonal edges.

3.2. Predicting

In order to arrive at a suitable predictor for the pixel \( x \), in the presence of diagonal edges of the nature illustrated in Fig. 3(c) and/or (d), we propose the use of the following averaging predictor,

\[
\hat{x} = \left( \frac{a + b + d}{3} \right) \tag{4}
\]

The use of this averaging predictor is justified due to the fact that in diagonal edge orientations similar to that illustrated in Fig. 3(c), the pixel \( x \) is highly correlated to pixels \( a, b \) and \( c \). In addition, the above predictor operates reasonably well at single pixel width diagonal edges of the nature shown in Fig. 3(d). Under such orientations, the fact that pixel \( d \) is considerably different from pixels \( a \) and \( b \), results in the average of these three pixels, \( a, b \) and \( c \), i.e. \( \hat{x} \), falling in between \( ab \) and \( d \). This acts positively in the sense that the gradient between \( \hat{x} \) and \( b \) (i.e. \( |\hat{x} - b| \) would show the same sign as compared to the sign of the gradient between \( d \) and \( b \) (i.e. \( |d - b| \)). This is a requirement for accurately predicting across a diagonal edge border that is oriented as shown in Fig. 3(d). Note that in the modified JPEG-LS prediction scheme proposed in Ref. [14], the identification and prediction of diagonal edges of this orientation was not possible.

In the proposed work, we have modified the edge detection/prediction strategy of JPEG-LS with the diagonal edge detection and prediction strategies proposed above. Note that under this scheme the diagonal edges are detected from among edges that would otherwise be categorized as vertical/horizontal edges (in original JPEG-LS) and not from areas, which would otherwise be considered as non-edge detected. The reasons for this have already been discussed.

4. Experimental results and analysis

In order to analyze the performance of the proposed algorithm, we performed experiments on a set of seven standard test images, namely, Baboon, Lena, Peppers, Barb, Clown, Camera and Bird.

The performance was measured in terms of percentage improvement of the Mean Squared Error of the Predicted image (PMSE), which is defined as follows:

\[
\text{% Improvement_of_PMSE} = \left( \frac{\text{PMSE}_{\text{JPEG-LS}} - \text{PMSE}_{\text{Proposed}}}{\text{PMSE}_{\text{JPEG-LS}}} \right) \times 100 \tag{5}
\]

where, \( \text{PMSE}_{\text{JPEG-LS}} \) and \( \text{PMSE}_{\text{Proposed}} \) are, respectively, the MSE of the predicted images, produced by JPEG-LS and the proposed technique. The PMSE for a given predicted image is defined as follows:

\[
\text{PMSE} = \frac{1}{N} \sum_{i=1}^{N} (x_i - \hat{x}_i)^2 \tag{6}
\]

where, \( N \) is the total number of pixels in the image and \( x_i \) and \( \hat{x}_i \) are, respectively, the original and predicted value of the \( i^{th} \) pixel. Thus better prediction would lead to higher values of the above relative performance measure.

For the purpose of comparison and the determination of absolute PMSE values of the predicted images obtained using the proposed scheme, in Table 1, we tabulate the PMSE values and lossless compression ratios of all test images, when compressed using JPEG-LS. Note that due to lossless reconstruction the MSE of the reconstructed image would be zero.

Fig. 4 shows the performance of the modified coder when the threshold \( T_1 \) is kept constant at \( T_1 = 11 \) and the threshold \( T_2 \) is changed within a range 0–50, in steps of 5. Even though ideally \( T_1 > T_2 \), in order to check the validity of the proposed scheme within a wider perspective, we perform the experiments within a wider range of values of \( T_2 \). The graphs of Fig. 4 clearly indicates that for most images when \( T_1 \) is held constant at \( T_1 = 11 \), the optimum performance is obtained when \( T_2 = 0 \). This is justifiable as at this setting of \( T_2 \), it follows that \( a = b \) (Eq. (3)) and

<table>
<thead>
<tr>
<th>Image</th>
<th>Compression ratio</th>
<th>PMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baboon</td>
<td>1.325:1</td>
<td>439.825</td>
</tr>
<tr>
<td>Lena</td>
<td>1.991:1</td>
<td>37.634</td>
</tr>
<tr>
<td>Peppers</td>
<td>1.773:1</td>
<td>74.010</td>
</tr>
<tr>
<td>Barb</td>
<td>1.690:1</td>
<td>213.777</td>
</tr>
<tr>
<td>Clown</td>
<td>1.702:1</td>
<td>94.242</td>
</tr>
<tr>
<td>Camera</td>
<td>1.851:1</td>
<td>215.706</td>
</tr>
<tr>
<td>Bird</td>
<td>2.307:1</td>
<td>22.847</td>
</tr>
</tbody>
</table>
the detected edge is most unlikely to be a horizontal or a vertical edge. Thus the edge would more accurately be classified as a diagonal edge and pixel $x$ would be predicted more accurately using the predictor of Eq. (4). However, for images, Clown and Camera, the optimum performance is when $T_2 = 15$ and $T_2 = 5$, respectively. These values are still justifiable as edge locations where $a$ and $b$ differ by such small margins could still be classified accurately as diagonal edges. However, for the image Clown, at the above optimum performance setting, $T_1 (= 11) < T_2 (= 15)$ and it remains to be seen whether this is actually the optimum pair, or whether the performance could be further increased for higher values of $T_1$. Fig. 5 illustrates the performance of the modified coder when the threshold $T_1$ is increased to $T_1 = 19$. For all test images, the performance with this higher threshold setting of $T_1$ shows clear improvements. This is justifiable as one requirement for identification of a diagonal edge is that $a$ and $b$, both differ by a considerable margin from $c$. This condition would lead to more accurate separation of diagonal edges from within a group of edges that would otherwise be categorized as vertical/horizontal edges. Closer investigation of Figs. 4 and 5 indicates that the modified coder performs more efficiently in coding images with higher percentages of diagonal edges, such as Peppers, Barb and Lena. This is predictable as JPEG-LS would perform badly in such images and the percentage improvement in prediction, brought upon by the proposed modification would thus be higher.

Fig. 6 shows the performance of the modified coder at the optimal $T_2$ setting for each image obtained from the experiments presented above. $T_1$ is varied between 3 and 41 for all images. The idea is to find the optimal threshold pair for each test image. The results thus obtained are summarized in Table 2. It shows that percentage improvements of PMSE of up to 15.66% are obtainable for the image set under consideration. It also justifies the fact that for all images, at the optimum performance setting, $T_1 > T_2$. Interestingly, this is so for the image Clown, which previously showed an optimum performance when $T_2 = 15$, while $T_1$ was held constant at 11. The optimum performance graphs of Fig. 6 also indicate that for very high values of $T_1$, for most test images, performance decreases below its optimum value. The reason for this is that at very high $T_1$ values, the percentage of edges that would be classified as diagonal edges reduces and the overall effect would be to lower the percentage improvements in the PMSE values. However, these graphs and the optimum performance settings indicate that $T_1 = 20$ and $T_2 = 0$, would be a good, compromised setting to obtain prediction improvements for all test image pairs. The use of only two parameters, which are easily deterministic, reduces the complexity of the proposed algorithm as compared to the techniques proposed in Ref. [14]. The percentage PMSE improvements that have been obtained by the proposed algorithm also outperform the percentage PMSE improvements that have been previously obtained by the method proposed in Ref. [14]. This is largely due to the more flexible approach of the proposed technique that eventually results in a more accurate identification of a larger number and variety of diagonal edges. The averaging predictor used also results in an overall improvement of the prediction accuracy in the presence of diagonal edges.

An interesting aspect, which can be observed from the results of the above experiments is that, although the proposed algorithm improves the accuracy of prediction, measured in terms of MSE values, the compression ratios stay the same. This is expected due to the fact that the entropy coding length is determined by statistical modelling.

### Table 2

<table>
<thead>
<tr>
<th>Image</th>
<th>PMSE JPEG-LS</th>
<th>PMSE proposed</th>
<th>Optimum % improvement</th>
<th>$T_1$</th>
<th>$T_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baboon</td>
<td>439.825</td>
<td>420.115</td>
<td>4.48</td>
<td>41</td>
<td>0</td>
</tr>
<tr>
<td>Lena</td>
<td>37.634</td>
<td>33.004</td>
<td>12.30</td>
<td>15</td>
<td>0</td>
</tr>
<tr>
<td>Peppers</td>
<td>74.010</td>
<td>62.420</td>
<td>15.66</td>
<td>25</td>
<td>0</td>
</tr>
<tr>
<td>Barb</td>
<td>213.777</td>
<td>188.240</td>
<td>11.95</td>
<td>31</td>
<td>0</td>
</tr>
<tr>
<td>Clown</td>
<td>94.242</td>
<td>91.945</td>
<td>2.44</td>
<td>19</td>
<td>15</td>
</tr>
<tr>
<td>Camera</td>
<td>215.7006</td>
<td>208.401</td>
<td>3.39</td>
<td>31</td>
<td>5</td>
</tr>
<tr>
<td>Bird</td>
<td>22.847</td>
<td>21.381</td>
<td>6.42</td>
<td>7</td>
<td>0</td>
</tr>
</tbody>
</table>
Algorithm, in Fig. 7, we illustrate the predictive error images corresponding to the smaller predictive errors. To this end, the reconstructed image quality could benefit by introducing smaller quantization steps corresponding to the smaller predictive errors. The specific advantage with JPEG-LS is that the number of context quantization regions could be reduced and more probabilities could be assigned around the center of the statistical distribution. Another impact upon compression efficiency by smaller predictive errors can be seen with the presence of fewer amounts of errors of lesser magnitudes, as compared to Fig. 7(a), which represents the predictive error image of JPEG-LS.

5. Conclusions

In this paper, we have identified a drawback in the JPEG-LS context classification/prediction scheme and have proposed a modification based on the accurate detection of diagonal edges and prediction of pixels in such neighbourhoods. Experimental results indicate that the proposed modifications reduce the PMSE up to 15% as compared with what is obtainable using the JPEG-LS standard scheme. The proposed modification maintains the low complexity requirement of JPEG-LS standard by adhering to the original prediction template proposed by JPEG-LS for context determination. Currently, experiments are underway to modify the statistical modelling part of the JPEG-LS scheme in order to obtain improved compression performance.

References