CHAPTER 3

A NEAR-LOSSLESS IMAGE CODER USING THE VISUAL QUANTISATION AND THE DPCM

3.1 GENERAL

Since the existing lossless techniques have low compression ratios, the alternative approach is to employ the near-lossless methods. In this Chapter, a new approach to the near-lossless compression of images with improved compression performance is described.

3.2 THE NEAR-LOSSLESS COMPRESSION

Consider a gray scale image of size MxN. Let $U(x,y)$ denote the original image where $0 \leq x \leq M$ and $0 \leq y \leq N$. Let $\hat{U}(x,y)$ denote the decompressed version of the same image. The objective of the near-lossless compression is to obtain $\hat{U}(x,y)$ as given in Equation (3.1) (Yea & Pearlman 2006).

$$\max |U(x,y) - \hat{U}(x,y)| \leq MAE, \ 0 \leq x \leq M, \ 0 \leq y \leq N$$  \hspace{1cm} (3.1)

The definition of the near-lossless compression given in Equation (3.1) is used in this work (Avcibas & Memon 2001). With this definition, the error information is user-defined, known in advance, and there is no uncertainty about the level of error in the reconstructed image. This is in
contrast to lossy compression systems where the error information is generally available after the decoding process only.

3.3 THE STANDARD NEAR-LOSSLESS CODERS

As per the ISO/ITU standard, the JPEG-LS is the standard coder for the lossless and near-lossless compression of still images. This coder exhibits good PSNR at high bit rates. The CALIC has a near-lossless option with higher compression ratio than the JPEG-LS coder, but the computational complexity is also higher. The JPEG-LS and the CALIC coders were explained in the previous Chapter.

Both these coders use context based predictors in their algorithms. However, the major drawback of these predictors is the computational cost. Although the JPEG-LS predictor is less complex than the CALIC predictor, the context modelling and the search for the optimum context are time-consuming processes in both the coders. Hence, new coders with simple predictors and simple algorithms are investigated in this work.

3.4 THE PROPOSED NEAR-LOSSLESS CODER

The proposed scheme is implemented as a two stage coder considering a near-lossless and lossless approach. The near-lossless layer is designed using a visual quantizer, which defines the amount of the near-lossless error as specified by Equation (3.1). The lossless layer is implemented using a block based DPCM encoder. The block based DPCM encoder processes the image block by block to generate a difference image. The difference image is entropy encoded using a Huffman coder. Inverse processes are applied at the decoder end to get the decompressed image. The complete coding process of the visual quantisation-DPCM (VQ-DPCM) based near-lossless coder is shown in Figure 3.1.
3.5 THE VISUAL QUANTISATION

The visual quantisation is an image pre-quantisation technique which introduces controlled error in an image. One of the primary requirements for the near-lossless image compression is the facility to introduce a user defined error in the image. It has been shown previously through experiments that, a 2% change in the contrast has been just visible and this requirement is equivalent to about 6 bits per pixel. This observation is utilised to generate visually quantized images.

In order to generate a visually quantised image, the intensity values in the images are first represented by their binary equivalents. The range of pixel values in an eight bit gray level image varies from 0 to 255. This means that, eight bits are required to represent each gray level. For introducing an error of MAE equal to one, the least significant position in the binary value of the gray level is made zero. This is equivalent to splitting the image into eight bit planes and clearing the bit plane 0. The last two bits of the pixel values are
cleared to get an error value of MAE equal to three. Effectively, the bit plane 0 and the bit plane 1 are filled with zeros. For an n-bit image, the removal of information from the bit plane 0 is equivalent to representing the pixels by using (n-1) bits. This technique is called as visual quantization in this work.

The net effect of visual quantisation is the reduction in the number of gray levels and an increase in the correlation of the adjacent pixels. The increased spatial correlation enhances the compressibility of the image and reduces the bit rate. The visual quantisation process is the only source of error in the encoding process. Large values of MAE are not recommended, as it will introduce visible distortion in the reconstructed image.

For example, let the gray level value 87 be represented as 01010111, using eight bits. This value becomes 86 (01010110) when MAE is equal to one. The difference in the original value and the quantised value is one. When the MAE value is equal to three, the gray level 87 is quantised to 84(01010100). The absolute value of the maximum possible error in the reconstructed image is three. Also note that the quantised value is always less than the original value. This is an advantage for medical images, where the background region contains gray level values between 0 and 2. The visual quantisation makes the background uniform, without generating any visible distortion.

In order to demonstrate the effect of visual quantisation on the background, a CT image is quantised with MAE equal to three. The zoomed part of the background in the original image and the visually quantised image are shown in Figure 3.2. Table 3.1 shows a few samples of gray level values before and after the visual quantisation operation, when MAE is equal to three.
Figure 3.2 Zoomed parts of the CT image

Table 3.1 The original and the quantized pixel values for MAE=3

<table>
<thead>
<tr>
<th>Original gray Level</th>
<th>Binary Value before quantisation</th>
<th>Binary Value After Quantisation</th>
<th>New Gray level</th>
<th>Change in Gray level</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>01010000</td>
<td>01010000</td>
<td>80</td>
<td>0</td>
</tr>
<tr>
<td>81</td>
<td>01010001</td>
<td>01010000</td>
<td>80</td>
<td>-1</td>
</tr>
<tr>
<td>82</td>
<td>01010010</td>
<td>01010000</td>
<td>80</td>
<td>-2</td>
</tr>
<tr>
<td>83</td>
<td>01010011</td>
<td>01010000</td>
<td>80</td>
<td>-3</td>
</tr>
<tr>
<td>84</td>
<td>01010100</td>
<td>01010100</td>
<td>84</td>
<td>0</td>
</tr>
<tr>
<td>85</td>
<td>01010101</td>
<td>01010100</td>
<td>84</td>
<td>-1</td>
</tr>
<tr>
<td>86</td>
<td>01010110</td>
<td>01010100</td>
<td>84</td>
<td>-2</td>
</tr>
<tr>
<td>87</td>
<td>01010111</td>
<td>01010100</td>
<td>84</td>
<td>-3</td>
</tr>
</tbody>
</table>
3.5.1 Algorithm for the Visual Quantisation

The algorithm for the visual quantisation technique is given below:-

Step 1 : Read the image  
Step 2 : Decompose the image into bit planes  
Step 3 : Get the value of MAE  
Step 4 : If MAE=1, clear the data from bit plane 0. If MAE=2, clear the data from bit plane 0 and 1 and so on.  
Step 5 : Assemble the bit planes back to get the visually quantised image

3.5.2 Histogram of the Images

The histogram of an image is a graph, which shows the number of gray levels present in the image and the number of pixels at each gray level. Consider an image which contains gray levels in the range \([0, L-1]\), where \(L\) is the maximum gray level present in the image. Let \(g_k\) be the \(k^{th}\) gray level in the image and \(n_k\) be the number of pixels having the gray level value \(g_k\). The histogram can be expressed as a discrete function of \(g_k\), as given in Equation (3.2).

\[
f(g_k) = n_k \quad (3.2)
\]

The histograms provide an insight into the gray level distribution of an image. They are widely used in image segmentation and image enhancement applications. In this work, histogram is used to illustrate the effect of the visual quantisation on the gray level distribution of the image. Figure 3.3 shows the histograms of an original MRI brain image and the visually quantised image.
It can be seen from Figure 3.3 that, the number of different gray levels are significantly reduced after the visual quantisation process. This reduction in the number of independent gray levels increases the compressibility of the image.

In order to illustrate the effect of the visual quantisation on the subjective quality of the image, the Lena image is visually quantised under various error conditions. Figure 3.4(a) shows the zoomed part of the hat of size 100x100 from the uncompressed Lena image. In Figure 3.4(b), the image
part is shown after clearing the LSB bits 0 and 1. The level of visual quantisation is increased further by clearing three LSB bits and four LSB bits of the pixels, and the resultant images are shown in Figures 3.4(c) and (d) respectively. The effect of the visual quantisation is not visible when two LSB bits are made zeros. However, the effect is clearly seen when four LSB bits are made zeros. The patches in the background region due to the loss of information are generally called as the artefacts.

Figure 3.4  Zoomed portions of the Lena image at various visual quantisation levels
Figure 3.5 shows the original image and the image decompressed after visually quantising the four LSB bits. The subjective quality of the image is good even after losing four bits of information from the pixels. This result proves that the human visual system based subjective analysis is not a good criterion to assess the quality of the visually quantised images. Hence, the objective criteria are preferred in this work for analysing the image quality.

![Original image and decompressed image](image1.png)

(a) Original image  (b) Decompressed image for MAE=15

**Figure 3.5 Subjective quality of the Lena image**

In order to analyse the effectiveness of the visual quantisation on the compression, the entropies of the original and the visually quantised images are determined. The entropy for the original image is 4.33 bits/pixel, while the entropy for the visually quantised image is 2.77 bits/pixel. The decrease in the entropy value is approximately 40% after the visual quantisation process.

### 3.6 THE BLOCK BASED DPCM CODER

One primary requirement for a telemedical application is to use an encoder with the minimal computational complexity. It is a known fact that
the complexity of a DPCM coder is less than that of the transform based coder. This observation has led to the use of a DPCM coder for image compression.

The DPCM is a spatial domain image compression technique, which is well suited to compress the images that exhibit good correlation between the neighbouring pixels. The correlation property is utilised to predict the pixels, and the difference information generated is sent to the entropy encoder. The pixels are predicted based on a weighted linear combination of the neighbouring pixels. One of the standard approaches for selecting the neighbouring pixels is to consider those pixels in the west, north and northwest positions. For example consider the image U of size MxN which contains pixels u(x,y). The predicted value of u(x,y) is given as (Gonzalez & woods 2002),

\[
\tilde{u}(x, y) = k_1u(x, y - 1) + k_2u(x - 1, y) + k_3u(x - 1, y - 1)
\]  

(3.3)

where \(k_1\), \(k_2\) and \(k_3\) represent the prediction coefficients and \(\tilde{u}(x,y)\) is the predicted pixel. The position of the neighbouring pixels used to calculate the value of \(\tilde{u}(x,y)\) is shown in Figure 3.6.

![Figure 3.6 Neighbouring pixels of u](image)

The error in prediction is given by Equation (3.4).

\[
e(x, y) = u(x, y) - \tilde{u}(x, y)
\]  

(3.4)
The prediction error is computed for all the pixels to get an error image, which is entropy encoded. Since the error image contains smaller amplitude values than the original image, only a less number of bits are required in the encoding stage.

In addition to the correlation between the adjacent pixels, typical low frequency images exhibit correlation between the neighbouring columns and the rows. Hence, instead of considering a small neighbourhood of pixels, the prediction operation can be extended to the image blocks, where a typical block is defined as one full row or column of the image. Another modification is the prediction coefficients used in the DPCM coder. The fractional prediction coefficients are not used; instead, all the predictor coefficients are assumed as unity. The absence of the fractional prediction coefficients leads to integer difference values, and is therefore suitable for the lossless operations. Since a complete row or column is considered for the prediction at a given instance, this approach is referred to as the block based DPCM.

3.6.1 **The Standard Block Based Predictor**

The main building block of a standard DPCM based coder is the predictor unit. Many DPCM predictors have been proposed for image coding applications, and they exploit the correlation property between the adjacent pixels. In this work, the correlation between the adjacent blocks is utilised to reduce the inter-block redundancies.

In a block based predictor, a difference block is generated by subtracting the adjacent image blocks. The block based predictor can be implemented as a lossy or lossless unit. The block based prediction in a lossy predictor is explained by considering an image \( U \) of size \( M \times N \). The image is divided into blocks of size \( M \times 1 \). Let the \( i^{th} \) block of the input image be a column vector \( x_k(i) \), which is expressed as  (Ke & Marcellin 1998),
where \( k=1..N \). Let \( d_k(i) \) and \( q_k(i) \) denote the prediction error block and the quantized prediction error block respectively. In the predictor feedback loop, \( \hat{e}_k(i) \) represents the de-quantized residual block and \( \hat{x}_k(i-1) \) is the predicted block. The operation of the block based DPCM is now described by Equations (3.6) to (3.10)

\[
d_k(i) = x_k(i) - \hat{x}_k(i-1) \tag{3.6}
\]

\[
q_k(i) = Q [d_k(i)] \tag{3.7}
\]

\[
\hat{q}_k(i) = Q^{-1} [q_k(i)] \tag{3.8}
\]

\[
\hat{x}_k(i) = \hat{q}_k(i) + \hat{x}_k(i-1) \tag{3.9}
\]

\[
\hat{x}_k(i-1) = D (\hat{x}_k(i)) \tag{3.10}
\]

The predictor is implemented using the delay block \( D \) as a one buffer delay of \( \hat{x}_k(i) \). Figure 3.7 shows the whole prediction process.

**Figure 3.7** The standard block based predictor unit
The DPCM predictor unit shown in Figure 3.7 is a lossy predictor in which the loss is controlled by the quantizer unit. A scalar quantisation unit is generally used by these encoders.

### 3.6.2 The Modified Block Based Predictor

In the modified implementation, the images are pre-quantised through the visual quantisation process. Hence, a lossless predictor is required only for encoding. The predictor is modified by repositioning the quantizer block and eliminating the inverse quantizer block. The pre-quantised image is fed to the summation block. The scalar quantizer is effectively replaced by the visual quantizer, which produces the near-lossless condition.

Let $y_k(i)$ denote the original image block. This block is visually quantised to produce the quantized block $q_k(i)$. Similar to the original implementation, the predicted block $\hat{x}_k(i-1)$ is obtained, as a one buffer delay of $x_k(i)$. The difference block $d_k(i)$ is generated by finding the difference between the predicted block and the visually quantised block. The modified predictor is described by Equations (3.11) to (3.13).

\[
q_k(i) = Q [y_k(i)] \quad (3.11)
\]

\[
d_k(i) = q_k(i) - x_k(i-1) \quad (3.12)
\]

\[
x_k(i) = d_k(i) + x_k(i-1) \quad (3.13)
\]

\[
x_k(i-1) = D (x_k(i)) \quad (3.14)
\]

Figure 3.8 shows the modified predictor incorporating the visual quantization block VQ.
A CT brain image is chosen to generate a sample difference image. The brain image is given as input to the visual quantizer to generate the pre-quantised image. The pre-quantised image is divided into columns and fed to the modified predictor unit to generate the difference blocks $d_k(i)$. The collection of all these difference blocks forms the prediction difference image. The original image and the prediction difference image generated by the proposed predictor unit are shown in Figures 3.9.

(a) Original image  (b) Difference image

Figure 3.9 The original and the difference CT brain image
Figure 3.10 shows the histograms of the prediction error image generated by the VQ-DPCM coder, before and after the visual quantisation. The number of prediction error levels has been significantly reduced in the histogram of the visually quantised image.

![Histograms of prediction error](image)

(a) Original  
(b) Visually quantised for MAE=3

Figure 3.10  Histograms of the prediction error of VQ-DPCM for the CT brain image

3.7  SIMULATION RESULTS AND DISCUSSION

A volumetric CT dataset consisting of 100 brain images is used to evaluate the compression performance of the VQ-DPCM coder. The size of each slice in the brain dataset is 256 x 256. In addition, sample slices of the kidney and thorax are also used for the comparison. The VQ-DPCM method is also applied to non-medical standard test images like Lena and Barbara. The bit rates are compared with the results of the CALIC. The CALIC has been chosen for the study, because it has a higher compression performance when compared to the JPEG-LS. Figure 3.11 shows the sample slices of the various medical images used for performance comparison.
The standard image quality metrics like the bit rate and the PSNR are used for analysing the performance of the VQ-DPCM coder. The coder developed by the McMaster University, Canada, which is available in the public domain, is used to get the CALIC bit rates. The performance comparison results are given in Table 3.2.
Table 3.2  Bit rate and PSNR comparison with the CALIC for various error bounds

<table>
<thead>
<tr>
<th>Image</th>
<th>Size</th>
<th>CALIC (MAE=1)</th>
<th>VQ-DPCM (MAE=1)</th>
<th>CALIC (MAE=3)</th>
<th>VQ-DPCM (MAE=3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>bpp</td>
<td>PSNR</td>
<td>bpp</td>
<td>PSNR</td>
</tr>
<tr>
<td>CT head 1</td>
<td>256 x 256</td>
<td>0.953</td>
<td>51.2</td>
<td>1.15</td>
<td>56.1</td>
</tr>
<tr>
<td>CT head 2</td>
<td>256 x 256</td>
<td>0.79</td>
<td>51.1</td>
<td>0.96</td>
<td>56.9</td>
</tr>
<tr>
<td>MR brain 1</td>
<td>256 x 256</td>
<td>2.08</td>
<td>50.5</td>
<td>1.71</td>
<td>55.3</td>
</tr>
<tr>
<td>MR brain 2</td>
<td>256 x 256</td>
<td>1.68</td>
<td>50.7</td>
<td>1.46</td>
<td>55.5</td>
</tr>
<tr>
<td>Kidney</td>
<td>414 x 360</td>
<td>2.78</td>
<td>49.9</td>
<td>1.77</td>
<td>53.2</td>
</tr>
<tr>
<td>Lena</td>
<td>256 x 256</td>
<td>2.66</td>
<td>49.8</td>
<td>1.96</td>
<td>54.1</td>
</tr>
<tr>
<td>Barbara</td>
<td>512 x 512</td>
<td>3.06</td>
<td>49.8</td>
<td>2.57</td>
<td>54.1</td>
</tr>
</tbody>
</table>

As per the data given in Table 3.2, when MAE is equal to one, both the PSNR and the bit rate are higher for the VQ-DPCM coder, than those of the CALIC. When the error is increased to MAE equal to three, the CALIC gives a higher PSNR value than the VQ-DPCM coder. However, the bit rate of the VQ-DPCM coder is lesser than the CALIC, which makes it quite suitable for compressing volumetric image datasets. The bit rate of the VQ-DPCM coder is lesser than the CALIC rates for the standard test images also.

In order to compare the bit rate and the PSNR of various near-ossless coders, the Lena image of size 512 x 512 is compressed, using the JPEG-LS, CALIC and the VQ-DPCM coder at various bit rates. Figure 3.12 shows the PSNR values obtained at different bit rates.
It can be inferred from Figure 3.12 that the VQ-DPCM coder gives a superior performance when compared to the JPEG-LS and CALIC at high bit rates. When the bit rate falls below 1.6 bpp, the PSNR of the VQ-DPCM coder is less than that of the JPEG-LS coder. However, the value of MAE is also high at this bit rate. Although the CALIC gives higher PSNR values than the other two coders, the complexity of the algorithm is also very high.

Another metric for assessing the image quality is the VSNR. The VSNR is calculated for the CT and MRI images separately for an MAE value of three, and separate graphs are plotted. Figure 3.13 shows the VSNR obtained for the VQ-DPCM coder, and the CALIC for the CT and MRI images. The VSNR values for the VQ-DPCM coder are better than those obtained for CALIC for both types of images. The VSNR metric proves that, for a given error bound, the images decompressed using the VQ-DPCM based near-lossless coder, have a better visual quality than those of the CALIC.
Since the VQ-DPCM coder is based on the visual quantization, a subjective observation is also performed. An uncompressed MRI brain image is considered for this purpose. It is compressed and decompressed, using the CALIC and the VQ-DPCM coder for a given error bound. The zoomed portions of the brain image decompressed using the CALIC and the VQ-DPCM coder are shown in Figures 3.14 (b) and (c) respectively. The decompressed images are perceptually indistinguishable from the original image, which is the expected result in the near-lossless condition.
In addition, the de-compressed images were shown to a medical expert. As per the expert’s observation, the decompressed images have better contrast than the original image.

![Original Image](image1.png)

(a) Original Image

![CALIC Image](image2.png)

(b) using CALIC

![VQ-DPCM Image](image3.png)

(c) using the VQ-DPCM coder

Figure 3.14  Zoomed part of the MRI Brain Image

3.8 CONCLUSION

A new VQ-DPCM based near-lossless image coder suitable for the compression of medical images is proposed in this Chapter. The visual
quantisation technique is applied to the medical images to make them near-lossless, and then they are encoded using a block based DPCM lossless coder. The medical images of different sizes and modalities are evaluated, and the results are compared with those obtained with the near lossless option of the CALIC and the JPEG-LS. Standard performance parameters like the bit rate and the PSNR values are calculated and compared. When MAE is equal to one, the PSNR value of the VQ-DPCM coder is higher by approximately 5dB than the CALIC technique for all the test images. The rate-distortion comparison results show that the PSNR values for the VQ-DPCM method are higher than those of the JPEG-LS at high bit rates.

The VSNR analysis results show that the proposed technique has superior performance than the CALIC. Besides, the proposed coder is context free, and hence requires a comparatively less amount of memory and computational resources. This is a significant advantage over the CALIC and the JPEG-LS coders, which require additional modules for context search and quantization. Due to the low complexity of the encoding and decoding algorithms, the proposed VQ-DPCM coder is well suited for tele-medicine applications.