Lossless Image Compression Based On Prediction and Contourlet Transform Methods

J N V R Swarup Kumar \#1, CH Venkateswara Rao \#2

1 MIEEE, Assistant Professor; 2 PG Student, Department Of CSE, Gudlavalleru Engineering College, Gudlavalleru, India.

Abstract:--The paper presents the lossless image compression based on prediction and contourlet transform methods in image processing. The lossless compression usually a less bandwidth or less memory and low compression ratio at the cost of image quality degradation. In the paper presents prediction and Contourlet transform methods are used. In prediction method, convert the color image to YUV and then apply the hierarchical scheme of upper, left, and lower pixels for the pixel prediction and arithmetic coding is added to the error signal corresponding to each context. In Contourlet transform has better convergence and finds the direct discrete-space construction to get flexible multiresolution, and better image compression. The experimental results show that the Contourlet transform reduces the bit rates compared with prediction method.

Keywords:-- Lossless color image compression, hierarchical prediction, context adaptive arithmetic coding and Contourlet transform.

I. INTRODUCTION

Lossy compression mainly consists of decorrelation and quantization stages that reduce the image size by permanently eliminating certain information. The RidGelet Transform (RGT) [1] was developed over several years in an attempt to break an inherent limit plaguing wavelet denoising of images. This limit arises from the frequently depicted fact that the two-dimensional (2-D) WVT of images exhibits large wavelet coefficients to represent the image edges. A basic model for calculating ridgelet coefficients is to view ridgelet analysis as a form of wavelet analysis in the Radon domain. It has been shown in [4] that ridgelet representation solves the problem of sparse approximation of smooth objects with straight edges. In [3], an attempt has been made to use RGT for image compression.

However, in image processing, edges are typically curved rather than straight and ridgelets alone cannot yield efficient representation. But, if one uses a sufficient fine scale to capture curved edges, such an edge gets almost straight, therefore ridgelets are deployed in a localized manner. As a consequence the Curvelet Transform (CVT) [4] has been introduced. CVT is based on multi scale ridgelets combined with a spatial band pass filtering operation. CVT was initially developed in the continuous-domain via multi scale filtering followed by a block RGT on each band pass image. Later, the authors proposed the second-generation CVT [2] that was defined directly via frequency partitioning without using RGT. Both curvelet constructions require a rotation operation for the frequency decomposition, which ensures the construction in the continuous-domain. For discrete images, sampled on a rectangular grid, the discrete implementation of the curvelet transform is very challenging.

Therefore a new image representation method was introduced: the Contourlet Transform (CTT) [5]. The authors start with a description of the transform in the discrete domain and then prove its convergence to an expansion in the continuous-domain. Thus a discrete-domain multiresolution and multidirectional expansion is constructed. This in the same way as wavelets is derived from filter banks, but using non-separable filter banks. Due to the fast-iterated filter bank algorithm the construction results in a flexible multiresolution, local and directional image expansion using contour segments [5]. However, CTT has the adverse property of showing other types of artifacts due to the discrete approach.

II. PREDICTION METHOD

Prediction error is the key role in image compression. The prediction method usually generates the low prediction error at edge or texture region, which increase the compression performance. An input RGB color image is convert into YUV color space and then apply the hierarchical scheme such as CALIC, JPEG-LS. It generates the upper, left, and lower pixels for the pixel prediction. The chrominance images U and V divided into even
subimage and odd subimage and apply prediction error of each sub image\((X)\). The hierarchical of prediction method as shown in fig.1.

\[
\begin{align*}
X(0) & \rightarrow X_e^{(1)} & \rightarrow X_o^{(1)} \\
X_o^{(1)} & \rightarrow X_e^{(2)} & \rightarrow X_o^{(2)}
\end{align*}
\]

Fig.1. Illustration of hierarchical decomposition

The prediction of sub image is given by

\[
e(i, j) = xo(i, j) - \hat{yo}(i, j)
\]

The prediction error as a random variable with probability distribution function (pdf) \(P(e|Cn)\), where \(Cn\) is the context coding that reflects the magnitude of edges and textures. Particularly, \(Cn\) is the level of quantization level of pixel activity \(\sigma(i, j)\) defined as

\[
\sigma(i, j) = |xe(i, j) - \hat{ye}(i + 1, j)|.
\]

The local activity is quantized into \(K\) steps such that \(Cn\) represents the step

\[
qn−1 ≤ \sigma(i, j) < qn
\]

for \(n = 1, \ldots, K\) with \(q0 = 0\) and \(qK = \infty\). The length of quantization level is determined such that each level includes the same number of elements (local activities).

For the compression of \(Xo\) pixels using \(Xe\), directional prediction level is employed to solve large prediction errors near the edges or regions. For each pixel \(xo(i, j)\) in \(Xo\), the horizontal predictor \(x\hat{h}(i, j)\) and vertical predictor \(x\hat{v}(i, j)\) are defined as

\[
\begin{align*}
\hat{x}_h(i, j) & = xo(i, j - 1) \\
\hat{x}_o(i, j) & = \text{round}\left(\frac{xe(i, j) + xe(i + 1, j)}{2}\right)
\end{align*}
\]

III. CONTOURLET TRANSFORM

The Contourlet Transform (CT) redundancy needs Laplacian pyramid decomposition stage. As a CT result we get two images, the first image on resulting from low pass approximation, and the second image on find the high pass approximation. These two images of details obtained (resulting from high pass) has always the same size of the immediately anterior, so we need not require resolution reduction. The directional decomposition is calculate with the detailed image, by that, if we made more pyramidal decompositions and generate at least a half more information of the above level as redundancies. So, In order to take benifits of the directionality offered by CT and to solve the redundancy, we need replace the Laplacian pyramid decomposition with Mallat decomposition. As DFB is not suitable to handle the low frequency content (Minh N.Do, and Martin Vetterli, 2005), it is important to combine the DFB with a multiscale decomposition, where the low frequencies of the image are removed before applying the DFB. This is the main idea behind a new transform called Contourlet Transform (CT) which is a non-redundant transform. For the CT it is important to ensure that we can find the perfect reconstruction of an image for the best case. The process to compute the CT is as follows (Vivien Chappelier, 2004):

1. calculate the DWT of an image, and in this work we use only \(\log_2\) (image size) -3 levels.
2. Design the directional filters, for this work we select the directional db5/3 filters.
3. Performs the directional decomposition using the selected images: LH, HL and HH. The process is made using the usual 5/3 tap filter that decomposes an image with a maximum of 3 directions or 8 subbands at the finer wavelet subbands.
4. Repeat the third step with the next wavelet level of LH, HL and HH images, in this work, we require the directional decomposition to the two high-frequency levels.
V. EXPERIMENTAL RESULTS

The compare the measurements of contour and prediction method as shown in table 1

<table>
<thead>
<tr>
<th>Prediction method</th>
<th>Contourlet transform</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compress ratio</td>
<td>1.1347</td>
</tr>
<tr>
<td>PSNR</td>
<td>66.3733</td>
</tr>
<tr>
<td></td>
<td>90.2178</td>
</tr>
</tbody>
</table>

Table 1. Measurement comparison

VI. CONCLUSION

In this paper we show the design and the implementation of a Contourlet transform and prediction method. The stages of the contour and prediction coder are: Contourlet transformation, directional filter deconstruction, hierarchical scheme, image compression and decompression. The possibility of coding images with directional detail preserving offers a wide range of applications in several industries in which this process is imperative such as medicine, mobile devices and face recognition. The objective measures such as PSNR is good appropriated to measure of CT compared to prediction method, this is due to the goal of the contour is to improve the measures but preserve directional features.

REFERENCES


