Comparisons of Image Compression Using Different Transformation Techniques

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Abstract — For image compression, it is very necessary that the selection of transform should reduce the size of the resultant data as compared to the original data set. For continuous and discrete time cases, wavelet transform and wavelet packet transform has emerged as popular techniques. While integer wavelet using the lifting scheme significantly reduces the computation time, a completely new approach for further speeding up the computation. First, wavelet packet transforms (WPT) and lifting scheme (LS) are used. Then an application of the LS to WPT is presented which leads to the generation of integer wavelet packet transform (IWPT).another technique is used for image compression is fractal image compression (FIC) is based on the partitioned iterated function system (PIFS) which utilizes the self-similarity property in the image to achieve the purpose of compression., the linear regression technique from robust statistics is embedded into the encoding procedure of the fractal image compression. Another drawback of FIC is the poor retrieved image qualities when compressing corrupted images, the fractal image compression scheme should be insensitive to those noises presented in the corrupted image. This leads to a new concept of robust fractal image compression.Another technique for image compression is new multi-layered representation technique for image compression, which combine Curvelet transform and local DCT in order to benefit from the advantages of each. Curvelet transform is one of the recently developed multiscale transform, which possess directional features and provides optimally sparse representation of objects with edges, but not for the textured feature. We exploit morphological component analysis (MCA) method to separate the image into two layers: piecewise smooth layer and textured structure layer, respectively associated to curvelet transform and local DCT. Each layer is encoded independently with a different transform at a different bit rate.

In this paper we are using following transformation techniques:
1. Discrete Cosine Transform (DCT)
2. Wavelet Packet Transform (WPT)
3. Discrete Wavelet Transform (DWT)

Keywords — compression, decompression, Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Wavelet Packet Transform (WPT).

I. INTRODUCTION:

Transform coding plays an integral component of contemporary image/video processing applications. Transform coding relies on the pixels in an image exhibit a certain level of correlation with their neighbouring pixels. Similarly in a video transmission system, adjacent pixels in consecutive frames [1] show very high correlation. Consequently, these correlations can be exploited to predict the value of a pixel from its respective neighbours. A transformation is, therefore, defined to map this spatial (correlated) data into transformed (uncorrelated) coefficients. Clearly, the transformation should utilize the fact that the information content of an individual pixel is relatively small i.e., to a large extent visual contribution of a pixel can be predicted using its neighbours.

A typical image/video transmission system is shown in Figure 1. The objective of the source encoder is to exploit the redundancies in image data to provide compression. In other words, the source encoder reduces the entropy, which in our case means decrease in the average number of bits required to represent the image. On the contrary, the channel encoder adds redundancy to the output of the source encoder in order to enhance the reliability of the transmission. Clearly, both these high-level blocks have contradictory objectives and their interplay is an active research area.
As mentioned previously, each sub-block in the source encoder exploits some redundancy in the image data in order to achieve better compression. The transformation sub-block decorrelates the image data thereby reducing (and in some cases eliminating) interpixel redundancy[3]. Here, it is noteworthy that transformation is a lossless operation, therefore, the inverse transformation results a perfect reconstruction of the original image.

II. THE DISCRETE COSINE TRANSFORM

Like other transforms, the Discrete Cosine Transform (DCT) attempts to decorrelate the image data. After decorrelation each transform coefficient can be encoded independently without losing compression efficiency. This section describes the DCT and some of its important properties.

A. The One-Dimensional DCT

The most common DCT definition of a 1-D sequence of length N is

\[ f(x) = \sum_{u=0}^{N-1} \alpha(u) c(u) \cos \left[ \frac{\pi(2x+1)u}{2N} \right] \]

\[ \alpha(u) \] is defined as

\[ \alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & \text{for } u = 0 \text{ and } u \neq 0 \end{cases} \]

for \( u = 0, 1, 2, \ldots, N-1 \). Similarly, the inverse transformation is defined as

\[ f(x) = \sum_{u=0}^{N-1} \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} \alpha(u) c(u) \cos \left[ \frac{\pi(2x+1)u}{2N} \right] \cos \left[ \frac{\pi(2x+1)v}{2N} \right] \]

for \( u, v = 0, 1, 2, \ldots, N-1 \) and \( \alpha(u) \) and \( \alpha(v) \) are defined.

B. The Two-Dimensional DCT

The 2-D DCT is a direct extension of the 1-D case and is given by

\[ \begin{align*}
    c(u,v) &= \alpha(u) \alpha(v) \cos \left[ \frac{\pi(2x+1)u}{2N} \right] \cos \left[ \frac{\pi(2y+1)v}{2N} \right] \\
    &\text{for } u,v = 0, 1, 2, \ldots, N-1 \text{ and } \alpha(u) \text{ and } \alpha(v) \text{ are defined.}
\end{align*} \]

The inverse transform is defined as

\[ \begin{align*}
    f(x,y) &= \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} \alpha(u) \alpha(v) c(u,v) \cos \left[ \frac{\pi(2x+1)u}{2N} \right] \cos \left[ \frac{\pi(2y+1)v}{2N} \right] \\
    &\text{for } u,v = 0, 1, 2, \ldots, N-1 \text{ and } \alpha(u) \text{ and } \alpha(v) \text{ are defined.}
\end{align*} \]
III. WAVELET PACKET TRANSFORM (WPT)

The wavelet transform enables analysis of data at multiple levels of resolution. In addition, transient events in the data are preserved by the analysis. When the wavelet transform (WT) is applied to a signal in the time domain, the result is a two-dimensional, time-scale domain analysis of the signal. The transform has proven useful for the compression and analysis of signals and images. The Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale.

The fast wavelet transform (FWT) is an efficient implementation of the discrete wavelet transform (DWT). The DWT is the WT as applied to a regularly sampled data sequence[6]. The transform of the data exhibits discrete steps in time on one axis, and discrete steps of resolution on the other. The superiority of the DWT over the discrete Fourier transform (DFT) is in the DWT's simultaneous localization of frequency and time, something that DFTs can't do. As a trade-off, the frequency divisions in the DWT are not in integral steps. Instead, the divisions are in octave bands. Each level of the transform represents a frequency range half as wide as the level above it and twice as wide as that of the level below it. Conversely, the time scale on each level is twice that of the level below it and half that of the level above it. This characteristic of the DWT poses problems when attempting to localize higher frequencies. Discrimination of frequency is sacrificed for time localization at the higher levels in the transform. It turns out that the DWT is actually a subset of a far more versatile transform, the wavelet packet transform (WPT). Developed by Dr. Ronald A. Coifman of Yale University, the WPT generalizes the time-frequency analysis of the wavelet transform. It yields a family of orthogonal transform bases of which the wavelet transform basis is but one member [7].

The wavelet packet transform is generalization of the wavelet transform. The wavelet transform applies the quadrature mirror filter (QMF) only to the lower frequency components repetitively. The wavelet packet transform applies the QMF not only to the lower frequency components but also to the higher frequency components. The tree algorithm for the wavelet packet transform can be represented as a full binary tree; see Figure 3.

Single wavelet packet decomposition gives a lot of bases from which you can look for the best representation with respect to a design objective. This can be done by finding the “best tree” based on an entropy criterion[8],[9].

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Fig.3. wavelet packet transform viewed as binary graph

DISCRETE WAVELET TRANSFORM (DWT)

The Wavelet Transform provides a time-frequency representation of the signal. It was developed to overcome...
the short coming of the Short Time Fourier Transform (STFT), which can also be used to analyze non-stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolution [11],[12].

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy. The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal.

The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.

In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales.

The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in figure 7[13]. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time multiresolution to discrete-time filters. In the figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G0 while the high pass filter is denoted by H0. At each level, the high pass filter produces detail information, d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n].

![Fig.4. Three level wavelet decomposition tree](image)

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. In accordance with Nyquist’s rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale.

With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The time-frequency plane is thus resolved as shown in figure 1.1(d) of Chapter 1. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition.

Figure 8, [14] shows the reconstruction of the original signal from the wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are up sampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain and the original signal. The Mallat algorithm works equally well if the analysis filters, G0 and H0, are exchanged with the synthesis filters, G11.
Fig. 5: Three level wavelet reconstruction tree

(a)

(b)

Fig. 6. (a) & (b) DWT Outputs

IV. CONCLUSIONS

After applying the different transformation like Discrete Cosine transformation and Discrete wavelet Transformation techniques we obtained the results as shown in the above figures (Fig: 7 & Fig: 8). These results are very efficient when compared to the various transformation techniques. Noise less and its resolutions of the images are improved after applying these techniques i.e DWT & DCT.

REFERENCES

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