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IMAGE COMPRESSION USING DISCRETE WAVELET TRANSFORM IN SIMULINK

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Abstract: With the advancement of technology and the entry into the digital era, world now have to deal with a massive amount of data on a regular basis, which can be tough. As a result, in order to be put to practical use, digital information must be stored and retrieved in an efficient and effective manner. Wavelets are a mathematical encoding technique that layer's information according to its level of detail. Approximations at various intermediate levels are made easier with this stacking. These approximations take up a fraction of the space that the genuine data does. A low-complex 2D image compression method employing wavelets as the basis functions is described, as well as a method for assessing the compressed image is presented.

Keywords: DWT, MSE, PSNR, IDWT, STFT

INTRODUCTION

Mobile computing is human-computer interact image compression is a type of data compression in which the original image is encoded with a small number of bits. The goal of picture compression is to eliminate image redundancy and store or transfer data in a more efficient manner. The fundamental purpose of such a system is to reduce the amount of data stored as much as feasible so that the decoded image displayed on the monitor is as close to the original as possible. Someone who has a web page or an online catalog with dozens or hundreds of photographs, for example, will almost certainly need to use image compression to store those images. There are various picture compressing technologies available today. This can be divided into two categories: lossless and lossy image compression. In exchange for considerably higher compression, lossy compression of data sacrifices some accuracy. A picture that has been recreated after lossy compression has degraded in comparison to the original. This is frequently due to the compression strategy fully discarding superfluous data. Under typical viewing conditions, there is little discernible loss. When it comes to visual images and digital voice, it works well. Here a lossy image compression method using discrete wavelet transform is analyzed using MATLAB Simulink.

WAVELETS

A signal's transform is simply another way of describing the signal. It has no effect on the information content of the transmission. The Wavelet Transform converts a signal into a time-frequency representation. It was created to address the shortcomings of the Short Time Fourier Transform (STFT), which is also capable of analysing non-stationary data. While the STFT maintains a consistent resolution across all frequencies, the Wavelet Transform employs a multi-resolution approach that analyses different frequencies with different resolutions. A wave is a periodic oscillating function of time or space. Wavelets, on the other hand, are localised waves. They are well adapted to the study of transitory signals because their energy is focused in time or space. Waves are used in Fourier Transform and STFT while wavelet transform uses wavelets of finite energy.

(a)

Fig.1 Wave

(b)

Fig.2 Wavelet

A wavelet is a wave-like oscillation whose amplitude begins at zero, grows, and then returns to zero. In general, wavelets are designed with specific qualities in mind that make them useful for signal processing. Wavelets can be merged with portions of an unknown signal using a "revert, shift, multiply, and sum" technique called convolution to extract information from the unknown signal. If the unknown signal contains information of similar frequency, the wavelet will resonate mathematically, just as a tuning fork physically resonates with sound waves of its unique tuning frequency. Many practical applications of wavelet theory rely on the concept of resonance. Wavelets are a mathematical tool that can be used to extract information from a variety of data types, including but not limited to audio signals and images.

The wavelet analysis is carried out in the same manner as the STFT analysis. The signal to be studied is multiplied with a wavelet function, similar to how a window function is multiplied in STFT, and then the transform is computed for each segment formed. Unlike STFT, the breadth of the wavelet function changes with each spectral component in Wavelet Transform. At high frequencies, the Wavelet Transform provides good time resolution but poor frequency resolution, while at low frequencies, it provides good frequency resolution but poor time resolution.

Discrete Wavelet Transform

The Wavelet Series is simply a sampled form of CWT, and depending on the resolution required, its computation might take a long time and demand a lot of resources. Wavelet Transform computation is shown to be faster when using the Discrete Wavelet Transform (DWT), which is based on sub-band coding. It is simple to implement and decreases the amount of time and resources required for calculation.

Techniques to decompose discrete time signals were devised in 1976, which laid the groundwork for DWT. Sub-band coding was developed as a result of similar work in voice signal coding. Pyramidal coding is a method that is comparable to sub-band coding and was created in 1983. Many enhancements to these coding systems were made afterwards, resulting in effective multi-resolution analysis techniques. Signals are examined in CWT utilizing a series of basic functions that are related to one another through basic scaling and translation. In the instance of DWT, digital filtering techniques are used to generate a time-scale representation of the digital signal. At various scales, the signal to be studied is passed through filters with various cutoff frequencies.

DWT AND IDWT OF IMAGE

A signal may be divided into approximations or averages and detail or coefficients using wavelet analysis. Averages are the signal's high-scale, low-frequency components. The low scale, high frequency components are the details. When we apply forward transform to a genuine digital signal, we get double the amount of data we started with. As a result, sampling must be done after filtering. The inverse procedure entails reassembling those components into the original signal without losing any information. This is referred to as reconstruction or synthesis. The inverse discrete wavelet transform is a mathematical operation that affects synthesis.

Fig.3 FDWT

The wavelet coefficients are used to rebuild the original signal. The wavelet reconstruction method requires up sampling and filtering, whereas wavelet analysis involves filtering and down sampling. The Forward DWT (FDWT) and Inverse DWT (IDWT) algorithms are presented in Figures 3 and 4, respectively. Different types of filters, such as db7, db4, and Haar, can be used to execute the FDWT on a signal. Here Haar wavelet transform is used to perform compression

Fig.4 IDWT

A low pass filter and a high pass filter are selected so that the frequency range between them is exactly halved. The analysis filter pair is the name for the filter pass. Each row of data is first subjected to a low pass filter, which extracts the row's low frequency components. The output data, however, only comprises frequencies in the first half of the original frequency range since the low pass filter is a half band filter. As a result, they may be sub sampled by two, resulting in output data with half the original number of samples. For the same row of data, the high pass filter is now applied, and the high pass components are similarly separated and placed to the side.

This step is repeated for each row. Following that, the intermediate data is filtered for each column. The resulting two-dimensional array of coefficients is divided into four bands, each labelled LL (low-low), HL (high-low), LH (Low-High), and HH (high-high) (High-High). The LL band can be decomposed in the same way, yielding more sub bands. This can be repeated up to any level, culminating in a pyramidal decomposition, as shown in figure 5.

The LL band at the top of the pyramid may be categorised as most significant, while the other detail bands can be classified as less essential, with the degree of significance decreasing from top to bottom. The compressed image will be obtained at low-low band as it is more promising compressed form and visually perfect to observe. The remaining bands will be having the other details like horizontal, vertical and diagonal details which are not essential and will be multiplied by zero during compression.

Fig.5 Flow of DWT

HAAR WAVELET

The simplest type of wavelet is a Haar wavelet. Haar wavelets are connected to a mathematical procedure known as the Haar transform in discrete form. All other wavelet transformations are based on the Haar transform. The Haar transform, like other wavelet transforms, divides a discrete signal into two half-length sub-signals. The first sub-signal represents a running average or trend, while the second is a running difference or fluctuation. The mother wavelet function of the Haar wavelet may be expressed as shown in figure 6

$$\psi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2}, \\ -1 & \frac{1}{2} \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

Its scaling function $\phi(t)$ can be described as

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

Fig. 6 Haar wavelet

The Haar wavelet transform has several advantages, including:

- It is theoretically simple
- It is fast.
- It is memory efficient since it can be computed in situ without the need of a temporary Array
- It is exactly reversible without the edge effects that plague other Wavelet transformations.

The Haar transform has various restrictions that might be problematic in specific applications. The Haar transform computes an average and difference on a pair of data while creating averages for the following level and each set of coefficients. The programme then shifts by two values and computes another average and difference for the following pair. All high frequency changes should be reflected in the high frequency coefficient spectrum. The Haar window consists of simply two components. If there is a significant shift from an even to an odd number, the change will not be reflected in the high frequency coefficients. Because the transform cannot condense the energy of the original signal into a few high-energy values above the noise threshold, audio de-noising via Haar wavelet is not always as successful. Also, when we try to utilise the Haar wavelet to compress the threshold of an audio sample, we receive terrible results. As a result, the Haar wavelet transform is ineffective for audio signal compression and noise reduction. Haar wavelet transformations can be performed using the Haar 2-tap wavelet.

IMPLEMENTATION USING SIMULINK

The implementation of the image compression using DWT is done in MATLAB Simulink software. The simulation done by using Simulink blocks. The block diagram is shown in figure 7.

Fig.7 Simulink block level design

An input image block is taken which accepts a RGB coloured image. Thereafter each individual R, G, B, are resized to 2^n rows because Harr DWT accepts inputs data which of 2^n rows only. After settings the rows and columns the signal is fed to DWT block. DWT block consists of series of LOW PASS and HIGH PASS filters which produce wavelet coefficients.

Here the test is done only at 2 level DWT which produces 4 sub-bands (HH, HL, LH, LL) where the compressed image is taken at LL band. The original image is reconstructed with the help of IDWT block. The output image size is again resized back to its original form with the same factor with which it is initially resized. The quality of the output image is calculated by PSNR (Peak Signal to Noise ratio) value and MSE (Mean Square Error) value. The higher the value of PSNR higher the quality. In order to view the output image and video viewer block is used.

RESULTS

The test is performed on a sparrow a colored image with 2 level haar wavelet. The results are as follows:

Fig.8 Original image

Fig.9 Compressed image

Fig.10 Reconstructed Image

Fig.11 Decomposition of Images after DWT

There are several methods for calculating the PSNR of a colour picture. Because the human eye is most sensitive to luma information, the PSNR for colour pictures may be calculated by converting the image to a colour system that isolates the intensity (luma) channel, such as YCbCr. In YCbCr, the Y (luma) indicates a weighted average of R, G, and B. Because the human eye sees G the most easily, it is assigned the most weight.

- i. The obtained PSNR value is 54.4 db
- ii. MSE is calculated from PSNR which is observed to be 0.23

APPLICATIONS

The above-mentioned Lossy Compression and Lossless compression technologies are utilised for picture compression applications. Image compression programmes employ a variety of approaches and algorithms to compress pictures. The choice of a method to compress photos among these two depends on the quality of the output that the consumers want. When consumers anticipate a very high-quality output from image compression apps without any data loss, the programme might employ a lossless compression approach.

When a great degree of precision is required, lossless compression methods are applied. Lossy compression can be utilised in some circumstances where quality is not as critical and can be compromised. When this compression technique is utilised, there will be very little loss in quality, and that loss will most of the time be invisible to the human eye. It can be employed in applications where a slight reduction in image quality is acceptable. Image compression is used in television broadcasting, remote sensing via satellite, military communication systems via radars, tele conferencing systems, computer-based communications systems, facsimile transmission, medical images in computer tomography magnetic resonance imaging, and capturing and transmitting satellite images, cameras, weather reporting etc.

CONCLUSION

In this study lossy image compression method has been discussed. There is wide research going on in the field of compression. This is possible by keeping in view the requirement of low bit rate methods for compression this study has been carried out. This study has found that there is more scope for research in this field to develop more efficient algorithms. There is more demand for compression algorithms and it is found that the research is to be made keeping in mind peak signal to noise ratio and compression ratio for better algorithms.

FUTURE SCOPE

The image compression can be taken to next step by implementing the same image compression on FPGA board thereby comparing the results with MATLAB and FPGA. This helps upgrading the image compression techniques. Using the same MATLAB Simulink other image processing like image fusion, lossless compression can be designed and analysed thereby also implementing them on FPGA boards.

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