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RESEARCH ARTICLE

A COMPARATIVE STUDY OF VARIOUS IMAGE COMPRESSION TECHNIQUES

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Abstract—: Image compression may be lossy or lossless. Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clip art, or comics. Lossy compression methods, especially when used at low bit rates, introduce compression artifacts. Lossy methods are especially suitable for natural images such as photographs in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that produces imperceptible differences may be called visually lossless. In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

Keywords— DWT, DCT, Harr Wavelets, Radon Transform, Inverse Radon Transform, SPHIT, Lifting Schemes

I. INTRODUCTION

In imaging science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The *acquisition* of images (producing the input image in the first place) is referred to asimaging. An image may be considered to contain sub-images sometimes referred to as regions-of-interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. In a sophisticated image processing system it should be possible to apply specific image processing operations to selected regions. Thus one part of an image (region) might be processed to suppress motion blur while another part might be processed to improve color rendition.

II. Various Image Compression Techniques

2.1 DISCRETE WAVELET TRANSFORM

Wavelet compression is a form of data compression well suited for image compression (sometimes also video compression and audio compression). Notable implementations are JPEG 2000, DjVu and ECW for still images, REDCODE, CineForm, the BBC's Dirac, and Ogg Tarkin for video. The goal is to store image data in as little space as possible in a file. Wavelet compression can be either lossless or lossy. Using a wavelet transform, the wavelet compression methods are adequate for representing transients, such as percussion sounds in audio, or high-frequency components in two-dimensional images, for example an image of stars on a night sky. This means that the transient elements of a data signal can be represented by a smaller amount of information than would be the case if some other transform, such as the more widespread discrete cosine transform, had been used.Wavelet compression is not good for all kinds of data: transient signal characteristics mean good wavelet compression, while smooth, periodic signals are better compressed by other methods, particularly traditional harmonic compression (frequency domain, as by Fourier transforms and related).

2.2 DISCRETE COSINE TRANSFORM

A discrete cosine transform (**DCT**) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient (as described below, fewer functions are needed to approximate a typical signal), whereas for differential equations the cosines express a particular choice of boundary conditions.

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample. There are eight standard DCT variants, of which four are common.

The most common variant of discrete cosine transform is the type-II DCT, which is often called simply "the DCT",[1][2] its inverse, the type-III DCT, is correspondingly often called simply "the inverse DCT" or "the IDCT". Two related transforms are the discrete sine transforms (DST), which is equivalent to a DFT of real and *odd* functions, and the modified discrete cosine transforms (MDCT), which is based on a DCT of *overlapping* data.

2.3 HAAR WAVELETS

In mathematics, the **Haar wavelet** is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an orthonormal function basis. The Haar sequence is now recognised as the first known wavelet basis and extensively used as a teaching example.

The **Haar sequence** was proposed in 1909 by Alfréd Haar.[1] Haar used these functions to give an example of an orthonormal system for the space of square-integrable functions on the unit interval [0, 1]. The study of wavelets, and even the term "wavelet", did not come until much later. As a special case of the Daubechies wavelet, the Haar wavelet is also known as **D2**.

The Haar wavelet is also the simplest possible wavelet. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as monitoring of tool failure in machines.

The Haar wavelet's mother wavelet function $\psi(t)$ can be described as

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

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

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

2.4 RADON TRANSFORM

In mathematics, the **Radon transform** in two dimensions, named after the Austrian mathematician Johann Radon, is the integral transform consisting of the integral of a function over straight lines. The transform was introduced in 1917 by Radon,[1] who also provided a formula for the inverse transform. Radon further included formulas for the transform in three-dimensions, in which the integral is taken over planes. It was later generalised to higher-dimensional Euclidean spaces, and more broadly in the context of integral geometry. The complex analog of the Radon transform is known as the Penrose transform.

The Radon transform is widely applicable to tomography, the creation of an image from the scattering data associated with cross-sectional scans of an object. If a function f represents an unknown density, then the Radon transform represents the scattering data obtained as the output of a tomographic scan. Hence the inverse of the Radon transform can be used to reconstruct the original density from the scattering data, and thus it forms the mathematical underpinning for tomographic reconstruction, also known as image reconstruction. The Radon transform data is often called a **sinogram** because the Radon transform of a Dirac delta function is a distribution supported on the graph of a sine wave. Consequently the Radon transform of a number of small objects appears graphically as a number of blurred sine waves with different amplitudes and phases. The Radon transform is useful in computed axial tomography (CAT scan), barcode scanners, electron microscopy of macromolecular assemblies like viruses and protein complexes, reflection seismology and in the solution of hyperbolic partial differential equations.

2.5 SET PARTITIONING IN HIERARCHICAL TREES (SPIHT)

SPHIT is an image compression algorithm that exploits the inherent similarities across the subbands in a wavelet decomposition of an image. The algorithm codes the most important wavelet transform coefficients first, and transmits the bits so that an increasingly refined copy of the original image can be obtained progressively.

III. PROPOSED WORK

In this paper an initial process of image compression is performed. The future work is to develop lossless compression algorithms in the field of medical image processing. In this paper a small algorithm is projected which is a combination of Harr and Wavelet Transform. Here initially an algorithm is developed that detects weather the blocks in the image is Homogeneous or Heterogeneous. For homogeneous block simple Discrete Wavelet Transform (DWT) is used, and for the heterogeneous block Lifting Wavelet Transform is used. In the Fig 3.1 an input image is fetched.

Fig 3.1 Input Image

Then the image is compressed using Discrete Wavelet Transform in order to compress it. During this compression the block decision is made and the compression technique is made according to it. Fig 3.2 represents the block decision and schemes that is adapted.

Fig 3.2 During Block Decision

Thus the image that is processed is recovered by inverse discrete wavelet transform. Fig 3.3 shows the output image and the PSNR value of the output image is 61.1296, which is comparatively a good result.

Fig 3.3 Output Image

IV. CONCLUSION

Digital image processing allows the use of much more complex algorithms, and hence, can offer both more sophisticated performance at simple tasks, and the implementation of methods which would be impossible by analog means. In particular, digital image processing is the only practical technology for Classification, Feature extraction, Pattern recognition, Projection, Multi-scale signal analysis.

Some techniques which are used in digital image processing include Pixelation, Linear filtering, Principal components analysis, Independent component analysis, Hidden Markov models, Anisotropic diffusion, Partial differential equations, Self-organizing maps, Neural networks, Wavelets. Thus here Wavelet transform and Harr are used to scale and process the images.

Here a very small portion of image compression is done and the theory that is repeated from various parts of internet is been again refreshed.

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