APPLICATION OF COMMUNICATION-CLUSTER TECHNOLOGIES IN PEDAGOGICAL INSTITUTIONS: INTERACTIVE METHODS OF PROCESSING GRAPHIC DATA

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ABSTRACT

The article discusses methods of compressing a graphical database for use in pedagogical facilities and institutions. Application of cluster systems to improve the quality of communication, transmission and storage of information.

Keywords: pedagogy, education, information technology, internet, cluster, information compression, quality, quality improvement methods.

INTRODUCTION

Images contain large amounts of information that requires much storage space, large transmission bandwidths and long transmission times. Therefore it is advantageous to compress the image by storing only the essential information needed to reconstruct the image. Wavelet analysis is very powerful and extremely useful for compressing data such as images and a lot of work has been done in the area of wavelet based lossy image compression. It's power comes from its multiresolution. Although other transforms have been used, for example the DCT was used for the JPEG format to compress images, wavelet analysis can be seen to be far superior, in that it doesn't create 'blocking artifacts'. This is because the wavelet analysis is done on the entire image rather than sections at a time. Wavelet analysis can be used to divide the information of an image into approximation and detail subsignals. The approximation subsignal shows the general trend of pixel values, and three detail subsignals show the vertical, horizontal and diagonal details or changes in the image. If these details are very small then they can be set to zero without significantly changing the image. The value below which details are considered small enough to be set to zero is known as the threshold. Thegreater the number of zeros the greater the compression that can be achieved. The amount of information retained by an image after compression and decompression is known as the "energy retained" and this is proportional to the sum of the squares of the pixel values. If the energy retained is 100% then the compression is known as lossless, as the image can be reconstructed exactly. This occurs when the threshold value is set to zero, meaning that the detail has not been changed. If any values are changed then energy will be lost and this is known as lossy compression.

Ideally, during compression the number of zeros and the energy retention will be as high as possible. However, as more zeros are obtained more energy is lost, so a balance between the two needs to be found.

Advantages of cluster systems in data compression

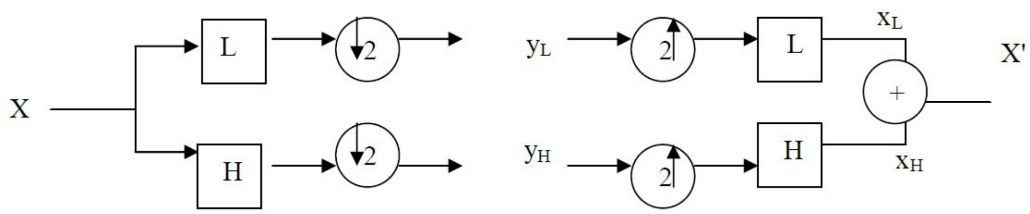
There are many different forms of data compression. This investigation will concentrate on wavelet transforms. Image data can be represented by coefficients of discrete image transforms. Coefficients that make only small contributions to the information contents can be omitted. Usually the image is split into blocks(subimages) of 8x8 or 16x16 pixels, then each block is transformed separately.

METHODOLOGY

However this does not take into account any correlation between blocks, and creates "blocking artifacts", which are not good if a smooth image is required. However wavelets transform is applied to entire images, rather than subimages, so it produces no blocking artifacts. This is a major advantage of wavelet compression over other transform compression methods.

Cluster-systems analysis

The best way to describe discrete wavelet transform is through a series of cascaded filters. The input image X is fed into low pass filter (L) and high pass filter(H) separately. The output of the two filters are the subsampled. The resulting low pass subband y_L and high pass subband y_H are shown in figure(1). The original signal can be reconstructed by synthesis filters (L) and (H) which take the up sampled y_L and y_H as inputs.



Figure(1). Wavelet decomposition and reconstruction process

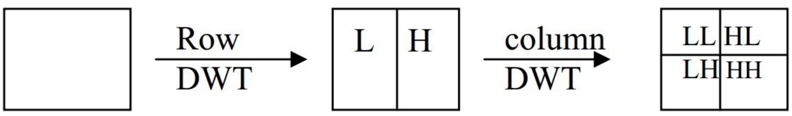
The mathematical representations of y_L and y_H can be defined as :

$$y_L(n) = \sum_{i=0}^{t_L} L(i)X(2n-i)........(1)$$

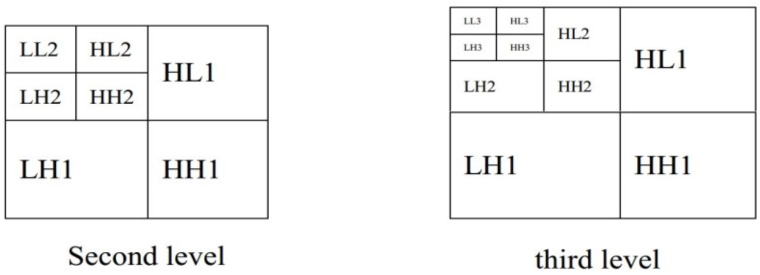
$$y_H(n) = \sum_{i=0}^{t_H} H(i)X(2n-i).........(2)$$

where t_L and t_H are the lengths of L and H respectively.

For a two dimensional images, the approach of the 2D implementation of the discrete wavelet transform(DWT) is to perform the one dimensional DWT in row direction and it is followed by a one dimensional DWT in column direction. See figure(2), in the figure, LL is a coarser version of the original image and it contains the approximation information which is low frequency, LH, HL, and HH are the high frequency subband containing the detail information. Further computations of DWT can be performed as the level of decomposition increases, the concept is illustrated in figure(3), the second and third level decompositions based on the principle of multiresolution analysis show that the LL1 subband shown in figure(3) is decomposed into four smaller subband LL2, LH2, HL2, and HH2.



Figure(2). 2D row and column computation of DWT



Figure(3): second and third level row and column decomposition

Numerous filters used to implement the wavelet transform, in present work we used the Daubechies filter whereas, the Daubechies basis vectors(forward and inverse transform), for 4x4 segments, are:

$$\text{Low pass: } \frac{1}{4\sqrt{2}}\left[1+\sqrt{3}, 3+\sqrt{3}, 3-\sqrt{3}, 1-\sqrt{3}\right]$$

$$\text{High pass: } \frac{1}{4\sqrt{2}}\left[1-\sqrt{3}, \sqrt{3}-3, 3+\sqrt{3}, -1-\sqrt{3}\right]$$

$$\text{Low pass}_{inv} = \frac{1}{4\sqrt{2}}\left[3-\sqrt{3}, 3+\sqrt{3}, 1+\sqrt{3}, 1-\sqrt{3}\right]$$

$$\text{High pass}_{inv} = \frac{1}{4\sqrt{2}}\left[1-\sqrt{3}, -1-\sqrt{3}, 3+\sqrt{3}, -3+\sqrt{3}\right]$$

The representation of f(x,y) at various resolutions can be done by a very simple iteration process. Moreover, the reconstruction of the original function from the coefficients of this representation is equally simple and fast.

DISCUSSION

Images are treated as two dimensional signals, they change horizontally and vertically, thus 2D wavelet analysis must be used for images. 2D wavelet analysis uses the same 'mother wavelets' but requires an extra step at every level of decomposition.

In 2D, the images are considered to be matrices with N rows and M columns. At every level of decomposition the horizontal data is filtered, then the approximation and details produced from this are filtered on columns.

At every level, four sub-images are obtained; the approximation(LL), the vertical detail, the horizontal detail and the diagonal detail (LH, HL, HH). As See Figure (3).

Cluster-systems compression and thresholding

For some signals, many of the wavelet coefficients are close to or equal to zero. Thresholding can modify the coefficients to produce more zeros. In Hard thresholding any coefficient below a threshold T, is set to zero. This should then produce many consecutive zero's which can be stored in much less space, and transmitted more quickly. To compare different wavelets, the number of zeros is used. More zeros will allow a higher compression rate, if there are many consecutive zeros, this will give an excellent compression rate. The energy retained describes the amount of image detail that has been kept, it is a measure of the quality of the image after compression. The number of zeros is a measure of compression. A greater percentage of zeros implies that higher compression rates can be obtained.

The number of zeros in percentage (PoZ) is defined by:

100 (number of zeros of the current decomposition)/ (number of coefficients).*

To change the energy retained and number of zeros values, a threshold value is changed. Thresholding can be done globally or locally. Global thresholding involves thresholding every subband (sub-image) with the same threshold value. Local thresholding involves uses a different threshold value for each subband.

RESULT

Definition of Wavelet compression is fix a non negative threshold value T and decree that any detail coefficient in the wavelet transformed data whose magnitude is less than or equal to zero (this leads to a relatively sparse matrix). Then rebuild an approximation of the original data using this doctored version of the wavelet transformed data. In the case of image data, we can throw out a sizable proportion of the detail coefficients in this and obtain visually acceptable results. This process is called lossless compression, when no information is loss (e.g., if T = 0). Otherwise it is referred to as lossy compression (in which case T>0). In the former case, we can get our original data back and in the latter we can build an approximation of it. We have lost some of the detail in the image but it is so minimal that the loss would not be noticeable in most cases.

The wavelet divides the energy of an image into an approximation subsignal, and detail subsignals. Wavelets that can compact the majority of energy into the approximation subsignal, therefore, the results calculated used global thresholding (threshold=STD of image), it was found to be a fair way of calculating threshold values.

The results proved to be more useful in understanding the effects of decomposition levels, wavelets and images. Changing the decomposition level changes the amount of detail in the decomposition. Thus, at higher decomposition levels, higher compression rates can be gained. However, more energy of the signal is vulnerable to loss. The quality of compressed image depends on the number of decompositions. The number of decompositions determines the resolution of the lowest level in wavelet domain provide the best compression. This is because a large number of coefficients contained within detailed subsignals can be safely set to zero, thus compressing the image. However, little energy should be lost.

Wavelets attempt to approximate how an image is changing, thus the best wavelet to use for an image would be one that approximates the image well.

CONCLUSION

The image itself has a dramatic effect on compression. This is because it is the image's pixel values that determine the size of the coefficients, and hence how much energy is contained within each subsignal. Furthermore, it is the changes between pixel values that determine the percentage of energy contained within the detail subsignals, and hence the percentage of energy vulnerable to thresholding. Therefore, different images will have different compressibilities.

To conclude, wavelets are useful for compressing signals but they also have far more extensive uses. They can be used to process and improve signals, in fields such as telecommunication where image degradation is not tolerated they are of particular use. They can be used to remove noise in an image.

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