High Speed Data Exchange Algorithm in Telemedicine with Wavelet based on 4D Medical Image Compression

Samreen Fatima
Student, Department of Electrical Engineering, Integral University, Lucknow, UP, INDIA

Corresponding Author: samreenfatima630@gmail.com

ABSTRACT
Existing Medical imaging techniques such as fMRI, positron emission tomography (PET), dynamic 3D ultrasound and dynamic computerized tomography yield large amounts of four-dimensional sets. 4D medical data sets are the series of volumetric images netted in time, large in size and demand a great of assets for storage and transmission. Here, in this paper, we present a method wherein 3D image is taken and Discrete Wavelet Transform(DWT) and Dual-Tree Complex Wavelet Transform(DTCWT) techniques are applied separately on it and the image is split into sub-bands. The encoding and decoding are done using 3D-SPIHT, at different bit per pixels(bpp). The reconstructed image is synthesized using Inverse DWT technique. The quality of the compressed image has been evaluated using some factors such as Mean Square Error(MSE) and Peak-Signal to Noise Ratio (PSNR).

Keywords—Discrete Wavelet Transform(DWT), Dual Tree Complex Wavelet Transform(DTCWT), SPIHT, MSE, PSNR

I. INTRODUCTION

Telemedicine is one of the potential areas in India that demands higher bandwidth and data rate for transmission of image and video sequences in real time. Telemedicine facility provides health care access to rural populations and remote areas and technical ministries under Government of India are experimenting telemedicine pilot project since last 15 years. As there are more than 75% of India’s populations across 29 states living in a landscape of 3 million square kilometer area there is a real need for telemedicine technology to be made available across the country. ISRO has deployed telemedicine nodes and is planning to expand telemedicine facility with the launch of a dedicated satellite called as HEALTHSAT (also known as GSAT-4) for this purpose. In order to preserve the high spatial resolution of medical images, large numbers of pixels/voxels are required to represent a medical image, where voxel is the basic element of the volumetric image just like a pixel of a 2D image [1]. Hence, the size of a medical image is usually very large.

Since extensive amounts of medical images are being produced by medical imaging techniques, this leads to a major memory storage problem, which is further exacerbated when dealing with 3D or 4D image data sets. Typically, even a few seconds of volume cardiac image sequences can consume a few hundred megabytes of storage space. For high-speed real-time telemedicine applications without loss in data, there is a need for use of hardware platforms for highly intensive processing algorithms such as DWT for image compression [3]. Figure 1 shows an Illustration of a 4D data set, which consists of n number of 3D frames. One of the possible solutions is use of hardware-software environment for telemedicine applications, wherein all complex processing algorithms that are computation intensive are deployed over hardware platforms and the front end is deployed on software platforms. With variation in data rate and image data resolutions, software platforms can be easily configured.

Figure 1: Illustration of a 4D Data set

Image compression aims to reduce the redundancy of the image data in order to be able to reduce the transmission rate of the image, in addition, it is useful to save the storage capacity and decrease the storage cost [2]. Image compression may be called lossy if we use a compression scheme method that leads to loss some image data that often not contribute too much to the visual quality of the image. Second method for compression called lossless if we use a method to maintain the image data without losing any visual quality of the image by rewrite the image data of the original image in more efficient way without redundancy of the data.

Medical imaging is the technique and process of creating a visual representation of the interior of a body for clinical analysis and medical intervention. Magnetic resonance imaging (MRI) is one of the medical imaging and...
part of biological imaging which use the imaging
technologies of X-ray radiograph and magnetic resonance.
It is used to investigate the anatomy and physical of the
body in both health and disease. The 3-D image described
an image that provides the perception of depth and it uses to
create.

II. DESIGN

This section covers the Algorithm design of DWT and DTCWT wavelet transforms.

A. DWT based Image Compression

Wavelet Transform of a function is the improved
version of Fourier transform. Wavelets transform allows the
components of a non-stationary signal to be analyzed. Wavelets are well localized in both time and frequency and
is reliable and better technique for the image compression
[5].

![Figure 2: Decomposition of a 3D Image at 3 levels](image)

The DWT based Image Compression technique is shown
in the figure 3 given below. An Image of Size
N*N*N is read at the input and then the pre-processing of
the Image is done [14]. Then the image is divided into 8
sub-bands using 3D-Discrete Wavelet Transform(DWT) at
decomposition level of 3, the size of the sub-bands reduces
by N/2*N/2*N/2 at every decomposition level as shown in
figure 2. Then for Compression of the Image 3D-SPIHT
encoding is done at different bit-per-pixel(bpp) values, at
the receiving end decoding is performed on the image
obtained at the output of SPIHT Encoding [6]. Then the
decoded image is reconstructed using the Inverse DWT,
where the original image is obtained.

The Mean Squared Error(MSE) and Peak-Signal
Noise Ratio(PSNR) are obtained at different bpp values.

![Figure 3: DWT based Image Compression Technique](image)

B. DTCWT based Image Compression

The Dual-tree complex wavelet transform (DTCWT). It calculates the complex transform of a signal
using two separate DWT decompositions (tree a and tree b) as shown in figure 4.

![Figure 4: Block diagram for a 3 level DTCWT](image)

If the filters used in one are specifically designed
differently from those in the other, it is possible for one
DWT to produce the real coefficients and the other the
imaginary [4]. This redundancy of two provides extra
information for analysis but at the expense of extra
computational power. It also provides approximate shift
invariance yet still allows perfect reconstruction of the
signal [7].

Here Pre-processing is done on an Image of size
N*N*N, which is the given to the Complex Dual Tree
function which divides the image into 64 sub-bands, which
is in the format of 4 octaves, where each octave has Real
and Imaginary parts as shown in figure 5.

Then Average of 4 octaves is taken and one single
octave is obtained, which is given to the SPIHT Encoder,
then the obtained output is transmitted, and at the Receiving
end decoding is done and then Inverse Complex Dual Tree
function is performed and the Original Image is obtained
[9]. The MSE and PSNR are obtained for different bits per
pixel values.

![Figure 5: Sub-bands obtained after performing Dual Tree
Complex Wavelet Function](image)
III. MATLAB IMPLEMENTATION

The propose system first decomposes original low-resolution input image into six complex valued high frequency sub-band images and low frequency sub-band images. DTCWT has been applied for preserving high frequency components of images [8]. As it has good directional selectivity and shift invariant property. As shown in fig. 3 original input image is decomposes using DTCWT, as it produces six complex valued high frequency sub-band images and low frequency sub-band images.

Then average of these sub-bands is taken and one single Octave is obtained, this is then given to the SPIHT [11] Encoder which has the following algorithm. The following sets of coordinates are used in the algorithm.

- $H(i, j)$ is the set of coordinates of the tree roots, which are the nodes in the highest wavelet level
- $O(i, j) = \{(2i, 2j), (2i, 2j+1), (2i+1, 2j), (2i+1, 2j+1)\}$ is the set of coordinates of the children of node $(i, j)$
- $D(i, j) = O(i, j)\setminus O(i, j)$ is the set of all descendants of node $(i, j)$
- $L(i, j) = D(i, j)\setminus O(i, j)$ is the set of descendants except the children of node $(i, j)$. To store the significance information three ordered sets are used. These sets are as given below:
- The coordinates of those coefficients, which are insignificant with respect to the current threshold, are contained in the list $LIP$ of insignificant pixels.
- The coordinates of those coefficients, which are significant with respect to the current threshold, are contained in the list $LSP$ of significant pixels.
- The coordinates of the roots of insignificant sub-trees are contained in the list $LIS$ of insignificant sets [12]. The sets of coefficients in $LIS$ are refined during compression and if the coefficients become significant they are moved from $LIP$ to $LIS$.

**3D-SPIHT Algorithm**

1) Initialize to the number of bit planes.
2) Set the $LSP$ as an empty list, and add the coordinates $(i, j)$ $H$ to the $LIP$, and only those with descendants also to the $LIS$, as type $A$ entry.
3) Sorting Pass:
   a. for each entry $(i, j, k)$ of the $LIP$
      i. If output $Sn(i, j, k) = 1$, move $(i, j, k)$ in $LSP$
      ii. output the sign of $c_{i,j,k}$
   b. for each entry $(i, j, k)$ of the $LIS$
      i. if the entry is type $A$ then
         1. output $Sn(D(i, j, k))$
      2. if $Sn(D(i, j, k))= 1$ then
         a. for all $(i', j', k') \in O(i, j, k)$ do:
            i. if output $Sn(i', j', k') = 1$ then
               1. add $(i', j', k')$ to the $LSP$
            2. output the sign of $c_{i',j',k'}$
         ii. else
            1. add $(i', j', k')$ to the end of the $LIP$
      b. if $L(i, j, k) \neq \emptyset$, move $(i, j, k)$ to the end of the $LIS$ as a type $B$ entry.
      c. else,
         i. remove $(i, j, k)$ from the $LIS$
      3. if the entry is type $B$ then
         a. output $Sn(L(i, j, k))$

![Figure 3: Design flow of Proposed System](image-url)
b. if Sn(L(i, j, k)) = 1
i. add all the (i′, j′, k′) ∈ O(i, j, k) to the end of the LIS as a type A entry
ii. remove (i, j, k) from the LIS
4) Refinement Pass: a. for all entries (i, j, k) of the LSP, except those included in the last sorting pass:
i. output the nth most significant bit of ci,j,k
5) Quantization-Step Update: decrement n by 1 and go to Step 3.a).

Then the Inverse SPIHT is performed and sub-bands are obtained [13] at the receiving end, where Reconstruction of the original Image is done using the Inverse DTCWT. Hence the Reconstructed Image is obtained.

IV. IMAGE QUALITY METRICS

(a) Compression Ratio (CR): It is defined as the ratio of original image to the compressed image and is given by
\[
CR = \left(1 - \frac{\text{Compressed Image Size}}{\text{Original Image Size}}\right)
\]

(b) Mean Square Error (MSE): It is used to measure the dissimilarities of reference image and distorted image pixels. It is given by
\[
MSE = \frac{1}{M * N} \sum_{i=1}^{M} \sum_{j=1}^{N} (X_{ij} - Y_{ij})^2
\]

Where X_{ij} and Y_{ij} are image gray values of reference. Image X and distorted image Y, M and N are the width and height of the image.

(c) Peak signal to Noise Ratio (PSNR): The PSNR is used to measure the quality of images [15]. It is given by
\[
PSNR = 10 \log_{10} \left(\frac{\text{peak value}}{MSE}\right)^2
\]

V. RESULT

The comparison of Mean Square Error of DWT and TCWT is tabulated.

| Bits per Pixel | DWT | DTCWT (encoding single octave) | DTCWT (encoding all the octaves) |
|----------------|-----|--------------------------------|---------------------------------|
| 0.6            | 675.54 | 671.49                        | 7866.72                        |
| 0.7            | 641.19 | 671.13                        | 7852.95                        |
| 0.8            | 512.36 | 671.03                        | 7742.76                        |
| 0.9            | 451.61 | 671.02                        | 7705.19                        |
| 1              | 477.78 | 671.02                        | 7635.93                        |

The comparison of Peak Signal to Noise Ratio for DWT and DTCWT is tabulated below.

| Bits per Pixel | DWT | DTCWT (encoding single octave) | DTCWT (encoding all the octaves) |
|----------------|-----|--------------------------------|---------------------------------|
| 0.1            | 2.30 | 17.26                          | 2.36                           |
| 0.2            | 9.25 | 20.48                          | 5.69                           |
| 0.3            | 16.03 | 19.68                        | 6.92                           |
| 0.4            | 17.25 | 19.84                          | 7.80                           |
| 0.5            | 18.52 | 19.84                          | 10.34                          |
| 0.6            | 19.84 | 19.86                          | 9.17                           |
| 0.7            | 20.07 | 19.86                          | 9.18                           |
| 0.8            | 21.06 | 19.87                          | 9.23                           |
| 0.9            | 21.61 | 19.87                          | 9.26                           |
| 1              | 21.37 | 19.84                          | 9.30                           |

VI. CONCLUSION

The Image compression is done using the Discrete Wavelet Transform and the Dual Tree Complex Wavelet Transform. The encoding of Image is performed using SPIHT Algorithm. Later, the reconstructed image is synthesized using Inverse DWT. The MSE and PSNR have been calculated at different bit per pixels.

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