Improving Compression Efficiency with Color Model Correlation based Cluster Coding in Visual Sensor Networks

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ABSTRACT
Camera based Sensor node operates under resource constraints, including energy supply, computation capability, storage space, and transmission bandwidth. Therefore, a low complexity image compression scheme is needed to compress image data without damaging its quality as long as possible. The proposed image compression is based on DWT with Color Space model. In this work, the correlation between the color channels are used to propose the new algorithm that contains YCbCr color space model. By using this method the size of the image with each iteration level is analyzed.

Keywords
Visual sensor Network, DWT (Discrete Wavelet Transform), CBCS-DWT (Correlation based color space DWT) Color channel, Color space.

1. INTRODUCTION
Recently Visual Sensor Network (VSN) has become one of the most interesting research topics in networking technologies. The VSNs are based on small camera sensor nodes and a sink. The main characteristics of such networks are nodes with scarce resources. Advances in visual sensors and wireless communication have enabled the development of low-cost, low-power visual sensor networks, which have recently emerged for a variety of applications, including environmental and Habitat monitoring, target tracking and surveillance. However, representing visual data requires a large amount of information, leading to high data rates, which in turn requires high computation and communication energy.

Consequently, visual sensor networks present several challenges beyond those common to low data rate sensing, such as acoustics, temperature or pressure. Camera based Sensor node operates under resource constraints, including energy supply, computation capability, storage space, and transmission bandwidth. Therefore, a low complexity image compression scheme is needed to compress image data without damaging its quality as long as possible. So compressing and transmitting images in a multihop method is considered.

Hence, a node does not have sufficient computation power to completely compress a large raw image. In this case, a distributed method to share the processing task is required to overcome the computation power limitation of each single node. By exploiting the characteristics of the Discrete Wavelet Transform (DWT), a distributed JPEG2000 image compression scheme is used, where nodes compress an image while forwarding it to the destination subject to a specific image quality constraint.

In this paper, a color based image compression method in VSNs is proposed, based on JPEG2000 image compression standard. This approach is based on discrete wavelet transform (DWT) and Correlation based color space (CBCS) which uses a better order of transmission for compress the color image. This paper is organized as follows: Section II describes the basics of Image Compression and section III describes Discrete Wavelet transform. The proposed color space model is described in section IV. Distributed task of image processing is studied in section V. Simulation results and performance issues are shown in Section VI. Finally, section VII concludes this work.

2. IMAGE COMPRESSION
Image compression is a technique, which is used to reduce the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. Image compression is achieved by exploiting redundancies in the image.

The redundancies could be spatial, spectral, or temporal redundancy. Spatial redundancy is due to the correlation between neighboring pixels. Spectral redundancy is due to correlation between different color planes. Temporal redundancy is due to correlation between different frames in a sequence of images such as in video-conferencing applications in broadcast images.

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. This is because 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. The Fig.1 shows the basic compression and decompression model.

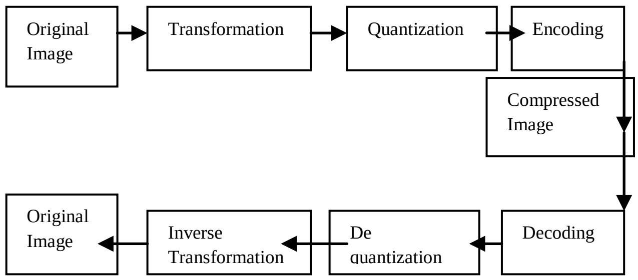


Fig 1: Compression and Decompression Model

2.1 Error metrics

Two of the error metrics used to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR).

The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are :

$$\text{MSE} = \frac{1}{MN}\sum_{Y=1}^{M}\sum_{X=1}^{N}\left[I(X,Y) - I'(X,Y)\right]^2$$

Equation (1)

$$\text{PSNR} = 20 \times \log_{10}\frac{255}{\sqrt{MSE}}$$

Equation (2)

Where I(x, y) is the original image, I'(x, y) is the approximated version (which is actually the decompressed image) and M, N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction.

3. DISCRETE WAVELET TRANSFORM

In many applications, wavelet-based schemes (also referred to as subband coding) outperform other coding schemes. Wavelet-based coding is more robust under transmission and decoding errors, and also facilitates progressive transmission of images. Because of their inherent multi-resolution nature, wavelet coding schemes are especially suitable for applications where scalability and tolerable degradation are important. Thus, we choose the new wavelet-based image compression standard JPEG2000 as the image compression scheme is this study.

Wavelet transform coding first transforms the image from its spatial domain representation to a different type of representation using wavelet transform and then codes the transformed values (coefficients).Wavelet Transform has become an important method for image compression. Wavelet based coding provides substantial improvement in picture quality at high compression ratios mainly due to better energy compaction property of wavelet transforms. Wavelet transform partitions a signal into a set of functions called wavelets. Wavelets are obtained from a single prototype wavelet called mother wavelet by dilations and shifting. The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies.

A signal is passed through a series of filters to calculate DWT. Procedure starts by passing this signal sequence through a half band digital low pass filter with impulse response h(n).Filtering of a signal is numerically equal to convolution of the tile signal with impulse response of the filter.

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k].\,h[n-k]$$

Equation (3)

A half band low pass filter removes all frequencies that are above half of the highest frequency in the tile signal. Then the signal is passed through high pass filter. The two filters are related to each other as

$$h[L-1-n] = (-1)^n g(n)$$

Equation (4)

Filters satisfying this condition are known as quadrature mirror filters. After filtering half of the samples can be eliminated since the signal now has the highest frequency as half of the original frequency. The signal can therefore be sub sampled by 2, simply by discarding every other sample.This constitutes 1 level of decomposition and can mathematically be expressed as

$$Y1[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]$$

Equation (5)

$$Y2[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n+1-k]$$

Equation (6)

Where y1 [n] and y2 [n] are the outputs of low pass and high pass filters, respectively after subsampling by 2.

This decomposition halves the time resolution since only half the number of sample now characterizes the whole signal. Frequency resolution has doubled because each output has half the frequency band of the input. This process is called as sub band coding. It can be repeated further to increase the frequency resolution as shown by the filter bank. (Fig 2)

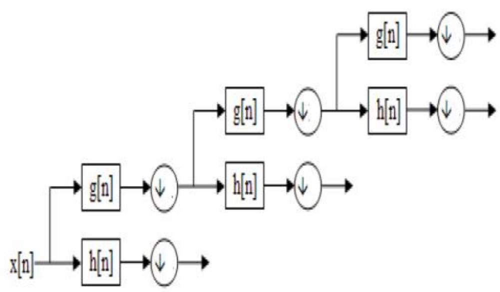


Fig 2: Filter Bank

The fundamental concept behind wavelet transform is to split up the frequency band of a signal (image in our case) and then to code each subband using a coder and bit rate accurately matched to the statistics of the band. There are several ways wavelet transforms can decompose a signal into various subbands. These include uniform decomposition, octave-band decomposition, and adaptive or wavelet-packet decomposition. Out of these, octave-band decomposition is the most widely used. This is a nonuniform band splitting method that decomposes the lower frequency part into narrower bands and the high-pass output at each level is left without any further decomposition.

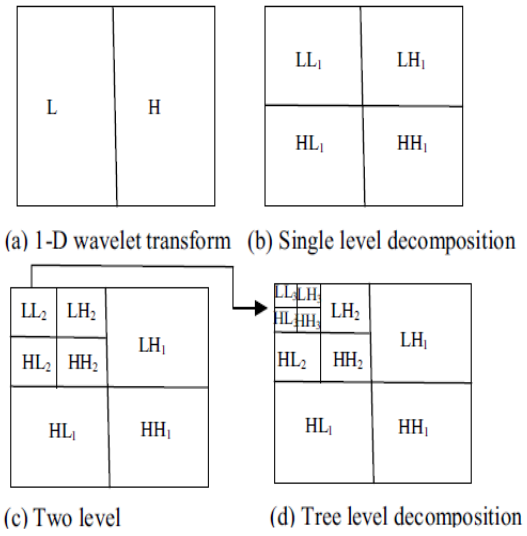


Fig 3: Discrete Wavelet Transform

The octave-band decomposition procedure can be described as follows. A Low Pass Filter (LPF) and a High Pass Filter (HPF) are chosen, such that they exactly halve the frequency range between themselves. First, the LPF is applied for each row of data, thereby getting the low frequency components of the row. When viewed in the frequency domain, the output data contains frequencies only in the first half of the original frequency range due to the LPF is a half band filter. Therefore, they can be sub-sampled by two according to Shannon's sampling theorem, so that the output data contains only half the original number of samples. Then, the HPF is applied for the same row of data, and similarly the high pass components are separated. The low pass components are placed at the left and the high pass components are placed at the right side of output row as in Fig. 3(a).

This procedure is done for all rows, which we term as 1-D wavelet transform. Next, the filtering is done for each column of the intermediate data. This whole procedure is called a 2-D wavelet transform. The resulting two-dimensional array of coefficients as in Fig. 3(b) contains four bands of data, each labeled as LL (low-low), HL (high-low), LH (low-high) and HH (high-high). The LL band can be decomposed once again in the same manner, thereby producing even more sub-bands as in Fig. 3(c). This can be done up to any level, thereby resulting in a pyramidal decomposition as depicted in Fig. 3.

4. PROPOSED ALGORITHM (CBCS-DWT)

In a color image, correlation exists between the neighboring pixels of each color channel and aswell as between the color channels. In the traditional color image compression algorithm the redundancy between the color channels are reduced by transforming them into a de-correlated color space. The most common way to describe what we see in terms of color is using combination of red, green and blue, which is referred as RGB color space.

A color space is simply a model of representing what we see in tuples. Y Cb Cr is one of the popular color spaces in computing. It represents colors in terms of one luminance component/luma (Y), and two chrominance components/chroma (Cb and Cr).

Y, Cb, and Cr are converted from R, G, and B as defined in CCIR Recommendation 601 but are normalized so as to occupy the full 256 levels of a 8-bit binary encoding. More precisely:

$$\mathbf{Y = 256 * E'y}$$

$$\mathbf{Cb = 256 * [E'Cb] + 128}$$

$$\mathbf{Cr = 256 * [E'Cr] + 128}$$

Where the E'y, E'Cb and E'Cb are defined as in CCIR 601. Since values of E'y have a range of 0 to 1.0 and those for E 'Cb and E 'Cr have a range of -0.5 to +0.5, Y, Cb, and Cr must be clamped to 255 when they are maximum value.

RGB to Y Cb Cr Conversion:

Y Cb Cr (256 levels) can be computed directly from 8-bit RGB as follows:

$$\mathbf{Y = 0.299\ R + 0.587\ G + 0.114\ B}$$

$$\mathbf{Cb = -\ 0.1687\ R - 0.3313\ G + 0.5\ B + 128}$$

$$\mathbf{Cr = 0.5\ R - 0.4187\ G - 0.0813\ B + 128}$$

Y Cb Cr to RGB Conversion:

RGB can be computed directly from Y Cb Cr (256 levels) as follows:

$$\mathbf{R = Y + 1.402\ (Cr-128)}$$

$$\mathbf{G = Y - 0.34414\ (Cb-128) - 0.71414\ (Cr-128)}$$

$$\mathbf{B = Y + 1.772\ (Cb-128)}$$

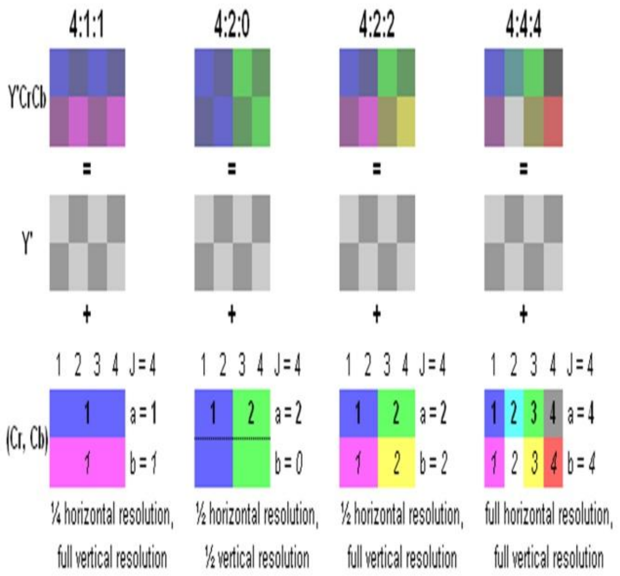


Fig 4: YCrCb color space Format

The YCrCb commonly used four subsampling schemes: 4:4:4, 4:2:2, 4:2:0, and 4:1:1. The 4:4:4 is actually full resolution in both horizontal and vertical directions, there's no subsampling done. 4:2:2 requires 1/2 resolution in horizontal direction; 4:1:1 requires 1/4 resolution in horizontal direction; and 4:2:0 means 1/2 resolution in both horizontal and vertical directions.

5. DISTRIBUTED TASK OF IMAGE COMPRESSION

The basic idea of the proposed distributed image compression is distributing the workload of task to several groups of nodes along the path from the source to the sink. The key issue in the design of distributed task of image compression is data exchange. In this proposition, data is broadcasted to all processors to speed up the execution time which may optimize network lifetime and increase the energy consumption. An example of distributed cluster-based compression using four nodes in each cluster is shown in Fig. 5.

Where applying the scenario proposed in IV and after receiving a query from a source node s, the cluster head c1 selects a set of nodes n1i (i = 1…4) in the cluster which will take part in the distributed tasks then informs source node, the first stage concerns the data partitioning scheme is parallel wavelet transform.

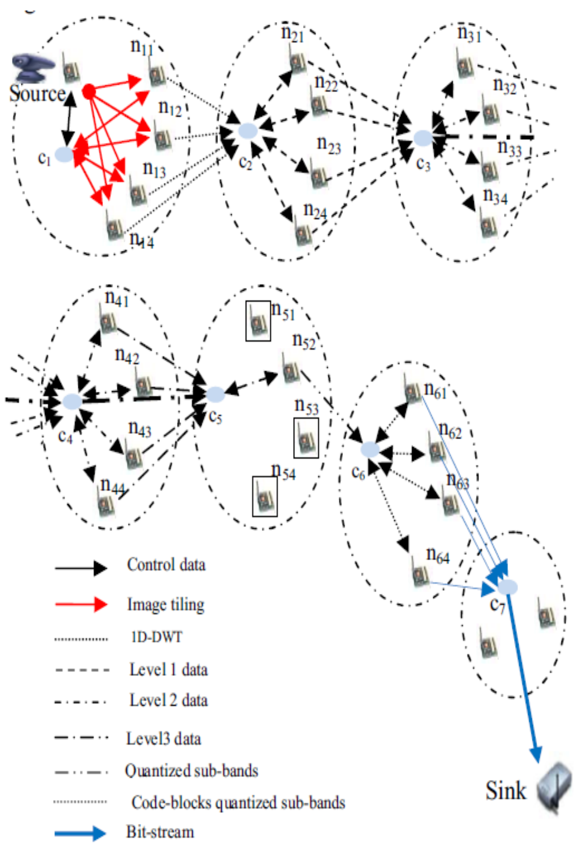


Fig 5: Distributed image compression

The source divides the original image into tile and transmits them to n1i (n11, n12, n13 and n14). Those nodes run 1D-DWT (horizontal decomposition) on their received data then send the intermediate results to c2. After receiving the results, c2 distributes it to the set of nodes n2i (n21, n22, n23 and n24). These nodes process data (vertical decomposition) and send the results (Level 1 data in Fig. 5(a)) to the next cluster head c3. The cluster head c3 chooses a part of the results (corresponding to LL1 in Fig. 5(b)) and distributes it to the set of nodes n3i (n31, n32, n33 and n34). Those nodes run 1D wavelet transform algorithm of LL1 subband then send the intermediate results to c3. After running the second 1D wavelet transform of LL1 sub-band, c3 process data and send the results (Level 2 data in Fig. 5) to the next cluster head c4. To be compatible with experiment results and depending on the image quality specified by the query (which is application-dependent), this procedure may continue on c4.

The cluster head c4 chooses a part of the results (corresponding to LL2 in Fig. 5(c)) and distributes it to the set of nodes n4i (n41, n42, n43 and n44). Those nodes run 1D wavelet transform algorithm on their received data (LL2 subband) then send the intermediate results back to c4 witch run 1D wavelet transform twice (corresponding to LL2 sub-band) and code the results (Level 3 data in Fig. 5 (d)). This procedure may continue on c7 and its following nodes until the final compressed image reaches the destination (sink) node.

It should be noted that, as shown in Fig. 6, after the DWT, all the sub-bands are quantized by a single node (n5i). The other nods are put awake. Since the quantization represents about 5,5% of the total process time, In spite of resource constraints, an individual node has a sufficient power to realize the quantization block. Given that the Tier- 1coding represents about 43% of the total process time, the tasks partitioning optimize the network lifetime. After receiving the results, c6 divides quantized sub-bands into a number of smaller code-blocks of equal size and send their processed results to set of nodes n6i (n61, n62, n63 and n64). In these nodes each code-block is entropy encoded independently to produce compressed bitstreams.

6. SIMULATION RESULTS & PERFORMANCE ANALYSIS

Color image compression is very important in today's communication era because most of the images are in color. Color images take more space for storage. Also without compression it may take long time for transferring images through network. Fig 6. shows the model used for compressing color images. **Matlab** software is used for simulating this work. In our analysis we have used Lena true color image (RGB 24 bit).

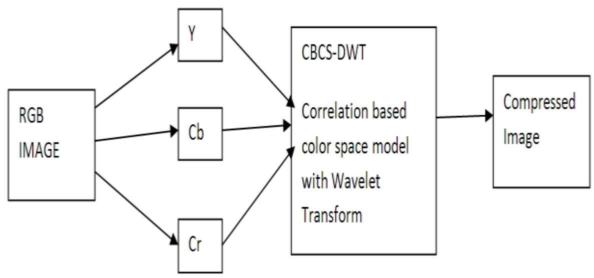


Fig 6: Image Compression Model

Image is converted to YCrCb format. Y′ is the luma component and CB and CR are the blue difference and red-difference chroma components. Y′ (with prime) is distinguished from Y which is luminance, meaning that light intensity is non-linearly encoded using gamma correction. Fig. 7 shows YCbCr image.

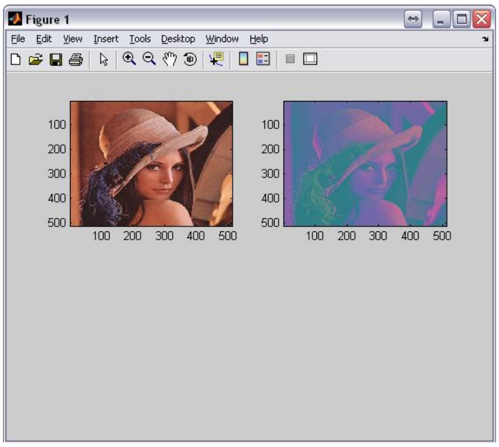
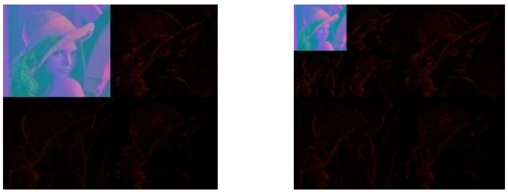
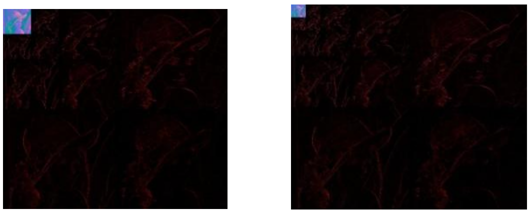


Fig 7: Results for RGB to YCbCr Compression



1-Level Decomposition **2-nd Level Decomposition**



3-Level Decomposition **4-Level Decomposition**

Fig 8: Results for 4 levels of decomposition

After converting RGB to YCbCr the Lena image is compressed using CBCS-DWT algorithm. Different decomposition level is used for analysis.

Table 1: Analysis for different decomposition levels

Original RGB size	YCbCr size	Level of Decompositio n	Compressed size
48.3kb	18.4kb	1	7.65kb
48.3kb	18.4kb	2	2.99kb
48.3kb	18.4kb	3	1.37kb
48.3kb	18.4kb	4	0.86kb

The origInal size of the 512 x 512 Lena image is 48.3kb.After YCbCr based color space compression image size is 18.4kb. There four levels of decomposition are analyzed and the efficiency of the compression algorithm is studied, which is shown in Table 1.

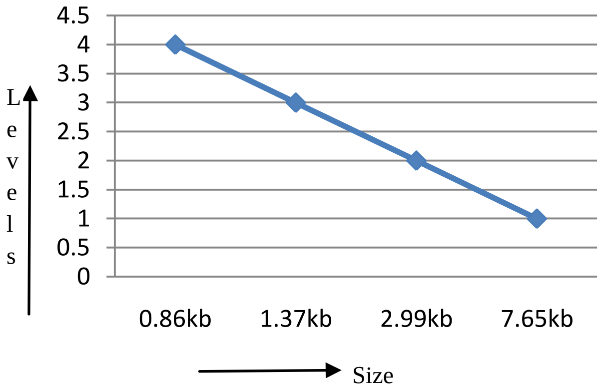


Fig 9: Decomposition level VS Compressed Size

Each level of decompositions are analyzed and the results of the compressed image size is plotted as in Fig 9, which shows that the compression efficiency is more at the high level of decomposition Better compression can be obtained with increased level of clusters with in the Visual Sensor Networks.

7. CONCLUSION

Compressing color images efficiently is one of the main problems in VSNs applications. Distribution based wavelet transformation is used for share the processing tasks. CBCS-DWT image compression algorithm was proposed in this paper. This algorithm provides better image compression in RGB image. The image size gets reduced greatly based on increasing the decomposition levels in cluster hierarchy. This work is extended with color based SPIHT to investigate the compression efficiency.

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