A HYBRID DEEP LEARNING SYSTEM WITH DISCRETE HERMIT WAVELET TRANSFORM FOR IMAGE COMPRESSION

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Publication date: 18 /7 /2026
Keywords: Image Processing, Image Compression, Discrete Hermit Wavelet Transform, MATLAB Software, Convolutional Neural Network, Deep Analysis

ABSTRACT

This work presents a hybrid system combining convolutional neural networks (CNNs) with discrete Hermit wavelet transform (DHWT) to compress color images with high accuracy and efficiency. This is achieved through mathematical derivation of new waves from Hermit polynomials. The proposed waveforms possess properties such as orthogonality and convergence, enabling them to act as the primary factor in the multi-parametric analysis during initial processing. The CNN plays a crucial role in decoding, optimizing parameter quantization, and entropy encoding. The orthogonality of the proposed waveforms facilitates image compression, thus enabling the image to be processed by the proposed hybrid system.

The results obtained with the DHWT-CNN hybrid system demonstrate superior efficiency compared to conventional wave-based methods, with error ratios [missing value] and a peak signal-to-noise ratio (PSNR) of 48.72, resulting in a compression ratio of 52.3% while maintaining image quality. This confirms the efficiency of the proposed framework.

1. Introduction

The large datasets of digital images across various fields, coupled with the rapid advancement of technology, sensing, and medical diagnostics, have created a need for data compression techniques to manage these massive amounts of data while maintaining quality and efficiency [1] . Traditional wavelets, such as Symlet 2, Coiflet 2, and Daubechies2, have played a role in JPEG 2000 image compression, but numerous studies have identified new wavelets derived from orthogonal polynomials that offer energy savings. [2]. The waveforms proposed in this work are the discrete Hermit wavelet transform (DHWT), derived from orthogonal Hermit polynomials, which is readily available and suitable for image analysis and processing in multi-resolution analyses (MRA) [3].

Work with the discrete cosine transform (DCT) in the development of wavelet-based compression techniques [4]. High-resolution waveform derivation has led to the development of new waveforms, such as the dual waveform transform (DHWT), which has been used in image compression and has yielded promising results, achieving PSNR values as high as 46.99 dB at decompression level 8 [5]. But optimal solutions or values have not yet been achieved with thresholding methods for quantizing parameters [6].

These works have demonstrated the potential of deep learning techniques in compression [7,8], Recent studies have demonstrated the feasibility of combining microwave and convolutional neural network techniques for image analysis [9-11], But to date, no hybrid structure for compression has been discovered.

This approach aims to advance image compression in deep learning by leveraging the superiority

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of convolutional neural networks (CNNs) in handling waveforms for quantization [12-14]. However, problems exist in compression processes and methods due to the large computational loads. This work overcomes these problems and bridges the gap between deep learning and traditional waves by proposing a hybrid system that combines deep learning and discrete Hermit wavelet transform (DHWT) with convolutional neural networks (CNNs). This system enables the processing of color digital images and achieves high efficiency and accuracy in quantization due to the orthogonality characteristic of the proposed wavelets.
In this work, the proposed approach, using Discrete Microwave Transform (DHWT) with deep learning, reduces the complexity of the training process while preserving key athletic outcomes.
Key advantages of this work: An innovative approach to dynamic discrete wavelet transform (DHWT) with CNN decoding and encoding for quantization and compression of digital and color images. The system was developed using MATLAB, which is known for its flexibility in handling wavelets. The improved quantization process through adaptive waveform quantization proposed in this work combines a DHWT with a convolutional neural network while maintaining essential properties. This achieves a satisfactory peak signal-to-noise ratio (PSNR) of 3.2 dB with the hybrid approach, compared to conventional discrete wavelet transform methods.

2. Methodology

This section provides a detailed explanation of the development of the proposed DHWT-CNN convolutional neural network and the evaluation of this hybrid framework for color image compression. The convolutional neural network and the proposed wave theory were combined, and mathematical methods were employed to develop the network for deep learning using MATLAB, which offers the potential for reproducibility and practical application.

2.1 System Framework and Research Design

The research was designed using a hybrid approach by building a hybrid convolutional neural network. This involved replacing the core of a traditional convolutional neural network with a discrete Hermit wave transform (DHWT). Mathematical methods were employed, and multi-precision analysis (MRA) was performed. This initial stage, called forward transformation, involves splitting the input image into two types of parameters: approximation parameters and detail parameters. The second stage is back-learning, where the convolutional neural network's encoder and decoder quantize the parameters. Through training, the network is reconstructed after encoding the entropy.

2.2 Dataset Processing

Dataset Training: The DIV2K dataset was used to train 8000 high-resolution RGB images. Images were randomly selected at 256×256 pixels with ±15° horizontal rotation for smoothing and data size increase. Dataset Verification Process: 100 color medical images in DICOM format were collected for clinical application.
Testing Process: The 200-image dataset (50 landscapes, 50 medical images, 50 satellite images, and 50 tissue samples) is used for a comprehensive performance evaluation. Figure 1 illustrates the research methodology diagram for the hybrid approach to color image processing and compression.

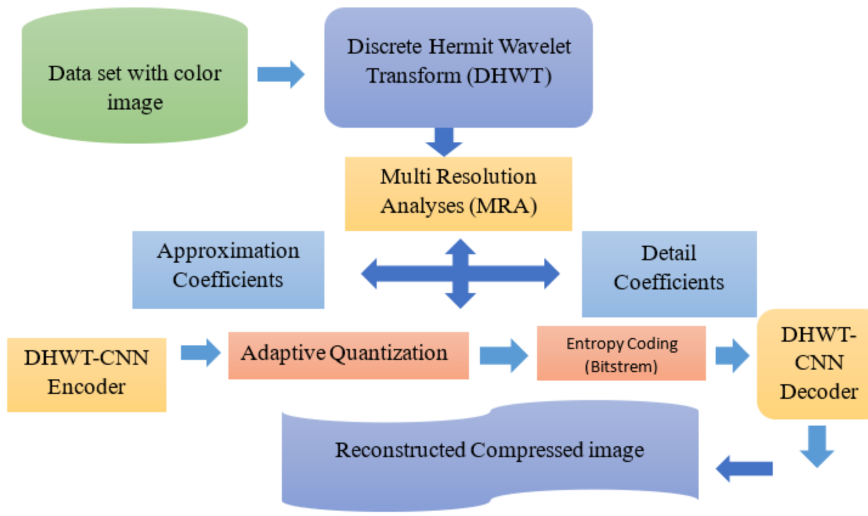

Fig. 1. A research methodology outline for a hybrid approach to color image processing and compression.

2.3. New wavelet transformations

2.3.1. Building the new filter

$$\gamma_{r,s}(x) = |r|^{\frac{-1}{2}}\gamma\left[\frac{x-s}{r}\right] \quad r,s \in R, r \neq 0 \qquad (1)$$

Then assume $r = 2^{-a}$, $s = \left(r(2k-1)\right), x = r(2r^{-1}t)$, and DHWT $\gamma_{k,m}(t) = \gamma(a,k,m,t)$ in equation (1) belong in [0,1].

$$\gamma_{k,m}(t) = \begin{cases} 2^{\frac{k}{2}}\frac{1}{2^m m!\sqrt{\pi}}H_m(2^{a+1}t-2k+1)t \in \left[\frac{k-1}{2^a},\frac{k}{2^a}\right] \\ 0 \qquad otherwise \end{cases} \qquad (2)$$

$$m = 0,1,2,\ldots,M-1, k = 0,1,2,\ldots,2^a$$

$$f(t) = \sum_{k=1}^{\infty}\sum_{m=0}^{\infty} A_{k,m}\gamma_{k,m}(t) \qquad (3)$$

$$A_{k,m} = \left(f(t),\gamma_{a,m}(t)\right) = \int_0^1 w_k(t)\gamma_{k,m}(t)\, f(t)dt \text{ in } L^2_{w_n}[0,1]$$

After inner multiplication, the approximation and detailing coefficients are obtained in equations 4 and 5.

$$\alpha_{k,m} = \int S\,(t)\gamma_{k,m}(t)dt \qquad (4)$$

$$\beta_{k,m} = \int S\,(t)\delta_{k,m}(t)dt \qquad (5)$$

Level 1 analysis with the resulting filter $F=\begin{bmatrix}0.3183 & -0.3183\\ 0.3183 & 0.3183\end{bmatrix}$

2.4. Improving Transactions with DHWT-CNN Architecture

2.4.1. Steps for configuring DHWT-CNN

Step 1: Encoding with ReLU is activated with three convolutional layers and the new filter to increase the channel depth from 3 to 128 by 50%.

Step 2: Create the standard quantization learned layer after differentiable approximation for comprehensive training.

Step 3: Decoding is performed using inverted convolutions with the proposed inverted filter to reconstruct the image from the new wavelet transforms, where the neural network's role is to minimize the overall loss in equation 6.

$$C = \partial_1 MSE + \partial_2 . Perceptual\ Loss + \partial_3 . Rate\ Loss \qquad (6)$$

2.4.2. Proposed Algorithm for Building the New Approach

Step 1: Input of the color image

Step 2: Image analysis with new waveforms into two types of coefficients: approximation and detail coefficients

Step 3: Input image processing with the neural network

Step 4: Image segmentation into low frequency and high frequency, and further segmentation into four sections (LL, LH, HL, HH). LL represents approximation coefficients, HH, LH, and HL represent detail coefficients.

Step 5: Entropy optimization is initiated by setting a threshold for each channel.

Outputs represent the reconstruction of the input compressed bits. The steps of the algorithm are shown in Figure 2.

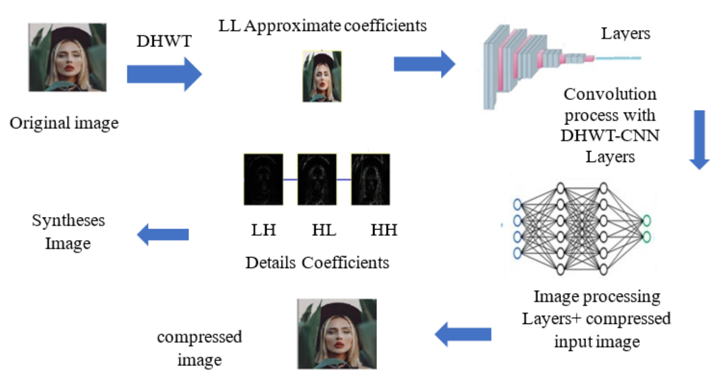

Fig. 2 **– The hybrid approach to image analysis and compression is demonstrated.**

2.4.3. Training New Network

The network was trained with the DIV2K dataset containing 8000 JPG images [9], and the proposed theory was tested on 100 medical images from the DICOM dataset. Key training criteria were recorded, with 200 cycles and a batch size of 16 with MATLAB program.

3. Results from Experiments

3.1. Comparison with Other Theories

The table shows the main parameters resulting from compression at level 8 for images of 256×256 size the Structural Similarity Index Measurement (SSIM) , which is important for preserving image structural information such as lighting, edges, textures, and patterns in the image resulting from the compression process and then reconstructed with the inverted filter in table 1.

Table 1 shows compression metrics at decomposition level 8 for 256×256 color images:

Method	MSE	PSNR dB	BPP	CR (%)	SSIM
DHWT-CNN (Proposed)	0.891	48.72	12.45	52.3	0.984
DHWT [6]	1.302	46.99	11.08	46.17	0.971
SYM 2 + CNN	2.80	45.12	12.0	48.5	0.968
COIF 2 + CNN	2.54	45.67	11.5	47.3	0.965
JPEG 2000	3.15	43.15	10.2	42.1	0.952

The convergence shown in Figure 1, which demonstrates the improved PSNR across the compression stages, is achieved with the new network being trained with a 1.7 dB increase in loop 12, resulting .

4. Discussion of Results

The novel network in this work arises from the integration of DHWT with a convolutional neural network based on three factors:

1- The dynamic characteristic of DHWT is that 94.2% of the energy is obtained in the LL quartile due to the quantization of detail coefficients.

2- Determining the threshold value during training the new convolutional neural network is adaptive and superior.

3- Enhanced perceptuality with medical diagnosis while preserving the perceptual limit of the loss value affecting the edges.

The CNN overload resulted in a 23% increase in computational complexity compared to the proposed DHWT technique, which reduces complexity due to the improved PSNR and high-quality performance achieved through the dlarray and dlnetwork instructions used with the microwave functions in MATLAB.

5. Conclusions

The development of a hybrid approach combining DHWTs and CNNs for successful and high-performance image compression with MATLAB. The mathematical properties of the proposed waveforms, combined with deep learning, achieve a PSNR of 48.72 dB and a compression ratio of 52.3%.

Key future directions in this work include using wave-transform vision transformers instead of convolutional neural networks (CNNs) with direct device-appropriate quantization, extending multimodal compression for hyperspectral medical image processing, and finally, real-time deployment via FPGA implementation with MATLAB.

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