A Novel Hybrid Image Compression Technique: Wavelet-MFOCPN

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Abstract: *In this paper a novel hybrid image compression technique is proposed. This technique inherits the properties of localizing the global spatial and frequency correlation from wavelets and classification and functional approximation tasks from modified forward-only counterpropagation neural network (MFO-CPN) for image compression. Several benchmark test images are used to investigate usefulness of the proposed technique. Experimental results of the proposed technique showed an enhancement in performance measures with respect to decoded picture quality and compression ratios, compared to the existing wavelet and neural network based image compression techniques*

Keywords: Wavelets; Modified Forward-only Counterpropagation; Clustering; Distance Metrics.

1 Introduction

In this rapidly changing world, image compression is one of the key components to compress the data for specified channel bandwidths or storage requirements maintaining the highest possible quality. The requirement of enormous expenditure on bandwidth and/or storage necessitates the use of various compression schemes.

To date, many compression techniques have been developed, such as transform image coding, predicative image coding and vector quantization. Among these, transform image coding is an efficient technique, particularly at low bit rates. For decades, JPEG, a DCT based image compression has been a standard of choice. However, Wavelet transforms have become the most prevalent techniques among those transform image coding techniques, as they are localized in both space and frequency domains [1].

Artificial neural networks are popular in function approximation, due to their ability to approximate complicated nonlinear functions [2]. The multi-layer perceptron (MLP) along with the back propagation (BP) learning algorithm is most frequently used neural network in practical situations [3]. Counterpropagation neural network (CPN) typically converges much more quickly than multilayer perceptrons (MLP), hence it is used as an alternative to the MLPs trained by BP. Many researchers have used correlation based techniques for clustering to forward-only counterpropagation network (FOCPN). This technique has some limitations, technique for overcoming these limitations are discussed in [4, 6]. In [5], modified FOCPN (MFO-CPN) using different distance metrics for selection of winner among the hidden layer neurons and non linear learning rates for better performance of the network is proposed.

MLP and MFO-CPN based image compression schemes are used for image compression applications but are limited to low compression ratio [5, 9]. Some recent papers show that the combination of neural network based approach and classical wavelet based approach leads to better compression ratio [7]. In this paper, we have integrated wavelet transform based image compression to MFO-CPN based image compression scheme. This integration leads to better compression ratio, preserving the image quality. Results obtained with proposed scheme are compared with classical wavelet based image compression schemes.

The organization of this paper is as follows. Section 2, concisely describes the wavelet transforms and MFOCPN. Section 3, describes the proposed methodology and its architecture. Simulation results and comparison of different wavelet transforms for different distance metrics are shown in section 4. Section 5, presents our conclusions.

2 Wavelet transforms and MFOCPN

2.1 Wavelet Transforms

Wavelet transform (WT) of an image represents image as a sum of wavelets on multi-resolution levels. Multi-resolution analysis is implemented via high-pass filters (wavelets) and low-pass filters (scaling functions).

In wavelet transform any one-dimensional function is transformed into a two-dimensional space, where it is approximated by coefficients that depend on time (determined by the translation parameter) and on scale, (determined by the dilation parameter). The zoom phenomena of the WT offer high temporal localization for high frequencies while offering good frequency resolution for low frequencies. Hence, the wavelet transform is well suited to image compression.

2.2 MFO-CPN

The architecture of MFO-CPN which is used in this work is discussed in [5]. The algorithm is shown in Figure 1.It uses several higher-order distance measures for clustering. It also incorporates nonlinear adjustment of learning rates in both the layers for faster convergence. In [5], results with different distance metrics are compared and ranked. It has been showed that higher order distances (Lm distance, Minkowsky), Euclidean, and Manhatten distances yields better results. Hence, these distances are considered in this work. Table 1, shows the details of these distance metrics.

Table 1: Distance metrics used for clustering

Minkowsky	$D(x,y)=\left(\sum_{i=1}^{m}\lvert x_i-y_i\rvert^r\right)^{1/r}$
Lm distance	$D(x,y)=\frac{\left(\sum_{i=1}^{m}\lvert x_i-y_i\rvert\right)}{\sigma}$
Euclidean	$D(x,y)=\sqrt{\left(\sum_{i=1}^{m}\left(\lvert x_i-y_i\rvert\right)^2\right)}$
Manhatten	$D(x,y)=\left(\sum_{i=1}^{m}\lvert x_i-y_i\rvert\right)$

3 Proposed methodology

In this paper, we explore the use of MFO-CPN networks to predict wavelet coefficients for image compression. In this method, we combined the classical wavelet based method with MFO-CPN. Instead of passing whole pixel values of Image we pass the significant wavelet coefficients obtained after applying wavelet transform to Image. Thus, this combination provides a better compression because at one stage compression is achieved by wavelet transform and in next stage we have compression with MFO-CPN. Both the schemes are shown in Figure 2 and 3.

Most wavelet-based signal compression systems are based on the structure shown in Figure 2. The wavelet coefficients are quantized (divided by a step size and then rounded to nearest integers), and are encoded without loss by the entropy encoder box, which usually employs contextual information. Higher amounts of compression are obtained by increasing the quantization step sizes (so that quantized values equal to zero are more likely), and by making better prediction for the ranges of quantized values via appropriate contexts and data structures. The other details regarding different blocks used in compression are given in [8].

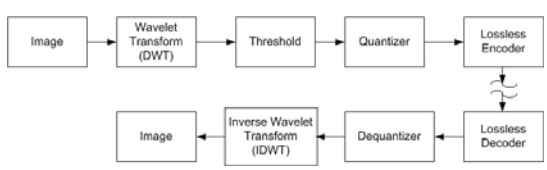

Figure 2: Block Diagram for Wavelet Based Image Compression

To achieve better compression we modified the above scheme and proposed a new scheme which uses the MFO-CPN after the wavelet transform block in Figure 2, the proposed scheme is shown in Figure 3. The MFO-CPN is used for predicting wavelet coefficients, and training is done for each wavelet level and subband which is obtained after applying the threshold. Applying thresholding is beneficial in the way that lower subbands of wavelets has significant information and we only need to learn these important information

In Figure 4, we show typical wavelet subband decomposition. The notation L and H stand respectively for lowpass and highpass filtering (the first letter denotes vertical and the second horizontal directions). The LL wavelets themselves work as smooth predictors (lowpass filters) and the LH, HL, and HH coefficients are the residuals computed from these predictors. The MFO-CPN basically acts as the function approximator and predicts the useful coefficients.

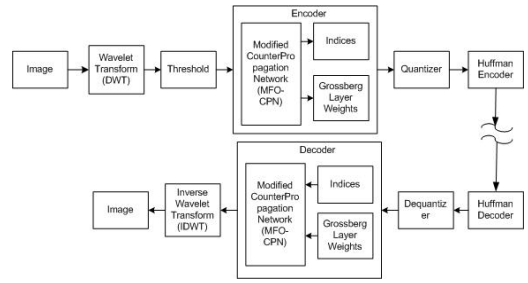

Figure 3: Block Diagram for Wavelet–CPN Based Image Compression

It requires less number of clusters to hold these values and we can store all the useful wavelet coefficients in these clusters indices and Grossberg layer weights. Instead of sending whole wavelet coefficients we now send the cluster indices and Grossberg layer weights which require less number of bits and we can achieve higher compression ratio. The algorithm mentioned in [5] is used for training of network. Similar to [5], we have used different distance functions to find out winner. The simulation results and comparison among all the distances and wavelet based methods are shown in next section. It has been found that performance with higher order distance function is better and it results in higher compression ratio.

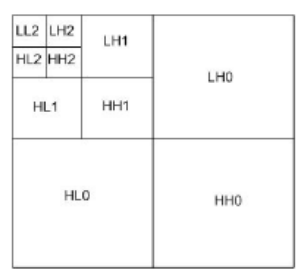

Figure 4: Multi-resolution wavelet representation (three levels shown).

4 Simulation Results and Comparison

In this section, simulation results for the proposed technique with three wavelets, namely, haar, daubechies 4, 6 (denoted as db4 and db6) for different distance metrics for Lena image of size 512 × 512 are shown. Quality measures such as PSNR and RMSE for decompressed image are calculated and compared at different distances. Table 2, shows the comparison of the results with the proposed hybrid technique to the classical wavelet based and MLP based image compression schemes.

5 Conclusion and Discussion

In this paper, we proposed a Wavelet-MFOCPN based technique for color image compression. The algorithm is tested on varieties of benchmark images. Simulation results for one of the standard image, i.e., Lena with different distance functions are presented. These results are compared with classical wavelet transform based image compression scheme. Several performance measures are used to test the reconstructed image quality. According to the experimental results, our technique outperformed the classical wavelet based image compression. It can be inferred from experimental results as shown in Table 2 that the higher order distance particularly, Lm distance performed well and results higher compression ratio. Besides higher compression ratio it also preserves the quality of the image, as it considers the standard deviation of the inputs to the network and clusters them with more accuracy when compared to other distances. It is observed that training of MFO-CPN with non linear learning rates, results in faster convergence of network.

The performance of proposed network is tested for three discrete wavelet transform functions, i.e., Haar, db4, and db6. Results for these wavelets are shown in Table 2. It is evident from this table that the highest image compression is achieved by using db6. For same number of significant coefficients Haar wavelet results in higher compression ratio but the quality of reconstructed image is not good. On the other hand db6 with same number of wavelet coefficients leads to higher compression ratio with good quality. In our analysis we found that the application of db6 wavelet in image compression out performs other two.

It can be concluded that the integration of classical with soft computing based image compression methods enables a new way for achieving higher compression ratio. As future prospects of proposed methodology we are extending this work for video compression applications.

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(a)

	Classical Wavelets	Wavelet – MFO-CPN with distance			
		Lm distance	Minkowsky	Manhatten	Euclidean
bpp	0.375	0.36	0.3629	0.3617	0.35
RMSE	10.1461	10.393	10.379	10.623	10.733
PSNR	28.0933	27.876	27.887	27.65	27.568

(b)

	Classical Wavelets	Wavelet – MFO-CPN with distance			
		Lm distance	Minkowsky	Manhatten	Euclidean
bpp	0.375	0.3380	0.3411	0.3356	0.3738
RMSE	10.2735	10.549	10.525	10.61	10.374
PSNR	27.9846	27.748	27.766	27.689	27.896

	Classical Wavelets	Wavelet – MFO-CPN with distance			
		Lm distance	Minkowsky	Manhatten	Euclidean
bpp	0.375	0.3018	0.3085	0.3044	0.3065
RMSE	10.274	12.854	12.677	12.764	12.694
(c) PSNR	27.985	26.033	26.175	26.097	26.152

Table 2: Comparison of performance measures of classical wavelet techniques (a) db6 (b) db4 and (c) Haar with the proposed technique for different distance metrics

Step 1: select the number of hidden layer neurons (h)

Step 2: initialize the *Kohonen* layer weights w_{ij} to random values within the interval bounded by the variations of input vector component.
Initialize the Grossberg layer weights v_{jl} to zero.
Initialize maximum number of iterations,
Initialize α to a large value but should be less than 1 and β to a value much less than 1 but it should be greater than 0.
Initialize weight error ε to very small value of order 10^{-4}.

Step 3: *while* {iterations < max iterations && *Kohonen* layer weight error > ε }
do {step 4 & step 5 }
otherwise {step 6}

Step 4: *for* each input pattern
{
do
{
Apply the each input attributes x_i to respective neurons in the input layer called input neurons. Calculate the distance ($nethz_j$) between the each input attributes x_i and weights w_{ij} connected to the respective hidden nodes using some distance function for each hidden neuron in hidden layer.
}
Calculate the output (z_i) of each hidden neuron in hidden layer using minimum distance criterion given by following:

$$z_k = \begin{cases} 1 & \text{if } nethz_k \le nethz_j, \text{ for all } k \\ 0 & \text{otherwise} \end{cases}$$

}

Step 5: update the weights in the *Kohonen* layer as follows

$$w_{ij}^{new} = w_{ij}^{old} + (z_j \times \alpha) \times (x_i - w_{ij}^{old})$$

i=1 to n (n=no. of input patterns)
j=1 to h (h=no. of hidden neurons in hidden layer)
}
Decrease α using following
$\alpha = \alpha$ - *small positive number*

Step 6: *while* {iterations < max iterations && *Grossberg* layer weight error > ε }
do {step 4 & step 7}
otherwise {step 8}

Step 7: update the weights in the *Grossberg* layer as follows

$$v_{jl}^{new} = v_{jl}^{old} + (z_j \times \beta) \times (y_l - v_{jl}^{old})$$

l=1 to m (m=no. of output patterns)
Increase β using following
$\beta = \beta +$ *small positive number*

Step 8: The network converged and successfully. Training is aborted.

Figure 1: Steps of algorithm for implementing the MFO-CPN