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# A Novel Enhanced Neural Network Model for Image Compression Using Wavelet – MSLLFOCPN

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## ABSTRACT

This work presents Wavelet-Modified Single Layer Linear Forward Only Counter Propagation Network (MSLLFOCPN) technique to solve image compression. In this technique, it inherits the properties of localizing the global spatial and frequency correlation from wavelets. Function approximation and prediction are obtained from neural networks. As a result counter propagation network was considered for its superior performance and the research enable us to propose a new neural network architecture named single layer linear counter propagation network (SLLC). The combination of wavelet and SLLC network were tested on several benchmark images and the experimental results shows that an enhancement in picture quality, compression ratio and approximation or prediction comparable to existing and traditional neural networks.

## Keywords

Wavelet; Modified Single Layer Linear Forward Only Counter propagation; Clustering; Distance Metrics.

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## 1. INTRODUCTION

Modern application requires high volume of data to accommodate large number of images. Image compression represents the process of data reduction and at the same time retains image information. The key components to compress the data are specified channel bandwidths or storage requirements and maintaining the highest possible quality. So efficient data compression techniques save storage space and accelerate the transmission time.

Till date, numerous image compression techniques discovered are transform image coding, predicative image coding and vector quantization. Out of these, transform image coding is an efficient technique particularly at low bit rates. JPEG and DCT based image compression has been a standard of choice for decades. However, wavelet transform becomes the most prevalent technique, since they are localized in both spatial and frequency domain [1]. Artificial neural network architectures are used to study the performance in function approximation and prediction due to their ability to approximate complicated function [2]. From the experimental tests, it was found that counter propagation neural network produce more accurate and converges much more quickly than other networks [3, 4]. The correlation based techniques were used by many researchers for clustering which is limited to forward only counter propagation network. This has its own limitations, the techniques to overcome these limitations are discussed in [5, 6]. As a result more attention was focused on modification which enhances the performance of counter propagation network. Some recent papers shows that the combination of neural network and classical wavelet based approach leads to better compression ratio [7]. In this work we have integrated wavelet transform to MSLLFOCPN based image compression. Results obtained with proposed technique leads to better compression ratio at the same time preserving the image quality.

This paper is organized as. Section II precisely deals about Wavelet and MSLLFOCPN. Section III describes proposed methodology and its architecture. Section IV tells about the simulation results and Section V views our conclusion.

## 2. Wavelet transforms and MSLLFOCPN

### 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 higher 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 MSLLFOCPN

The original forward-only counter propagation network shown in fig.1 has only one output unit per each output element. So the cluster has only one average value that represents the average of the correct output value y associated with the input vector value x that cause the cluster to win the competition. This will limit the net capabilities to produce specific output values instead of approximating a function that interacts with the input vectors to determine the output values. The objective of the net is to approximate a continuous function that maps a subset of n-dimensional Euclidean space into the real numbers. Vector functions can be handled by creating one network per output coordinate.

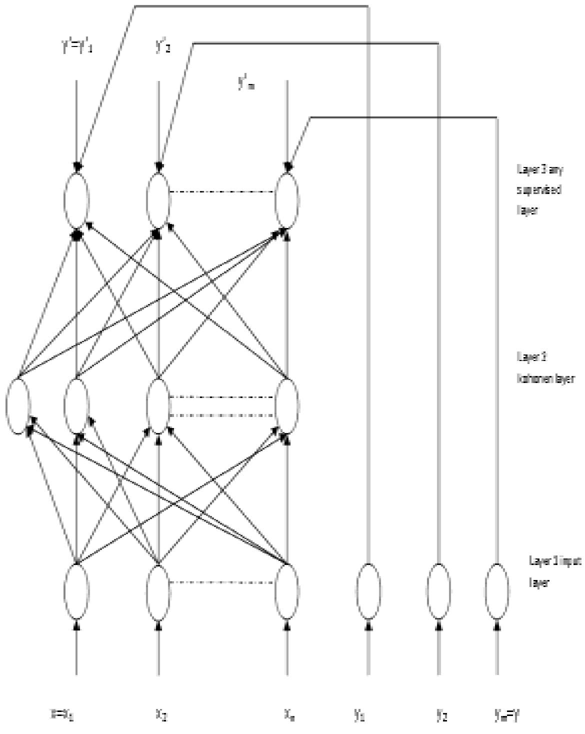


Fig 1. The forward-only counter propagation network

The modification to the original counter propagation network was accomplished by constructing a network for each cluster. Each cluster's network will approximate a supervised learning. As first step, the constructed network will be multi-layered network with two hidden layers network with two hidden layers since cybenko showed that two hidden layers network with continuous sigmoid non linearity can approximate any continuous function arbitrarily well on a compact set. The resulting modified counter propagation network is shown in fig.2. Figure 3shows the structure of the two hidden layered networks referred to in fig 2.

As a further refinement, the two hidden layers of the network of fig 3 is replaced by single layer linear network. Although the former is more robust than the later the single layer linear net is simpler, require less processing elements, does not need a normalization process and it is easily understood. In single layer linear network robustness can be achieved by increasing number of clusters in the network.

The final resulting architecture of the single layer linear counter propagation network show in fig 4 consist of a number of cluster's each of these clusters contains single processing elements that approximate a function for the subset of examples associated with that cluster.

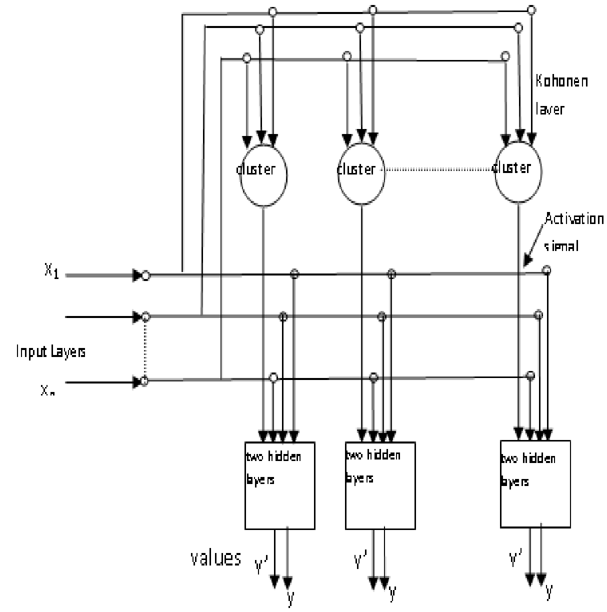


Fig. 2. Modified single layer linear counter propagation network

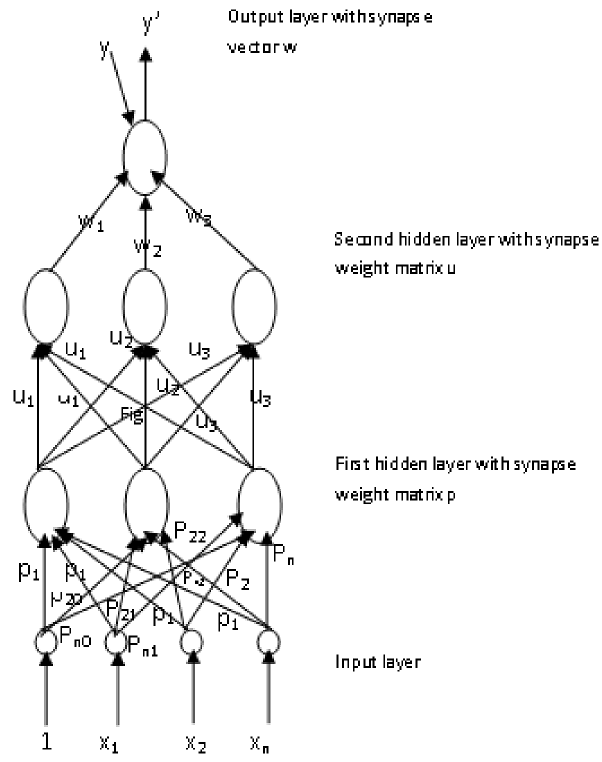


Fig. 3. Structure of the two hidden layer

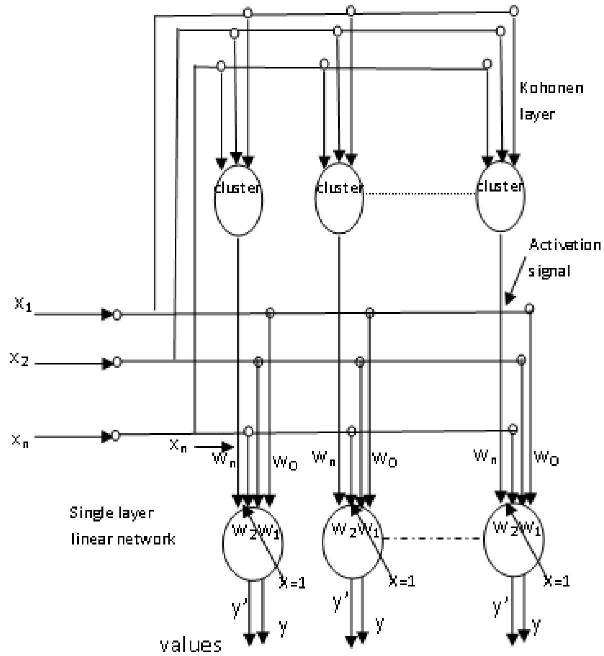


Fig.4:The final structure of SLLIC

## 3. Proposed Methodology

In this paper the use of MSLLFOCPN networks is explored to predict wavelet coefficients for image compression. In this method, we integrate the classical wavelet based method with MSLLFOCPN. Instead of passing whole pixel values of image we pass the significant wavelet coefficients obtained after applying wavelet transform to image. This provides better compression because at one stage compression is achieved by wavelet transform and in next stage compression is done by MSLLFOCPN. Both figures are shown in fig 5 & 6.

Wavelet based compression systems are shown in figure 5. The wavelet coefficients are quantized and are encoded without loss by entropy encoder box, which usually has contextual information. Higher amounts of compression are obtained by increasing the quantization step sizes and by making better prediction for the ranges of quantized values via appropriate contexts and data structures.

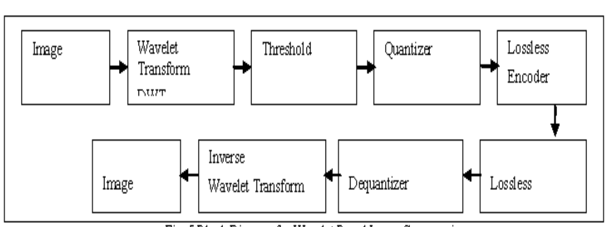


Fig 5 Block Diagram for Wavelet Based Image Compression

To achieve better compression MSLLFOCPN is used after wavelet transform block shown in figure 6. The MSLLFOCPN is used for predicting wavelet coefficients and training is done for each wavelet level and sub band which is obtained after applying the threshold. Applying threshold is beneficial, that lower sub bands of wavelet has significant information and we only need to learn these important information.

Figure 7 shows typical wavelet sub band decomposition. The notation L and H stand respectively for low pass and high pass filtering. The LL wavelet themselves act as smooth predictors and LH, HL and HH coefficients are the residuals computed from these predictors. The MSLLFOCPN basically works as the function approximator and predicts the useful coefficients.

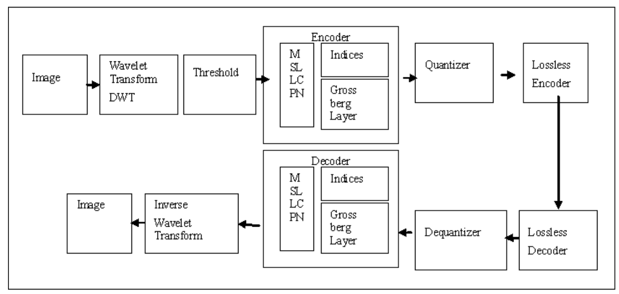


Fig. 6 Block Diagram for Wavelet – CPN Based Image Compression

It requires less number of clusters to hold these values and we can store all the useful wavelet coefficients in these cluster 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 used for training of network and Euclidean distance function to find out the winner is presented in figure 8.

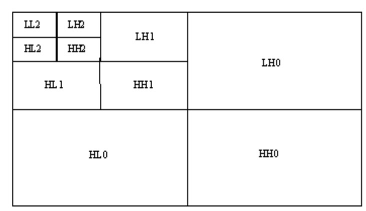


Fig. 7. Multi-resolution wavelet representation (three levels)

## 4. Simulation Results and Comparison

In this section, simulation results for the proposed technique with three clusters (namely 32, 64 and 128) of different image size for cameraman (256 x 256, 512 x 512) are shown. Quality measures such as PSNR and MSE for decompressed image are calculated and compared. Table 1 & 2, shows the comparison of the results with the proposed technique to the existing modified forward only counter propagation network.

## 5. Conclusion and Discussion

In this paper, the proposed technique is used for image compression. The algorithm is tested on varieties of benchmark images. Simulation results for one of the standard image, i.e., Cameraman with different clusters are presented. These results are compared with existing technique. Several performance measures are used to test the reconstructed image quality. According to the experimental results, the proposed technique outperformed the existing wavelet based image compression. It can be inferred from experimental results as shown in Table 2 that the higher order distance particularly 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. 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.

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Fig.8. Algorithm for implementing Modified Single Layer Linear Counter Propagation Network

Phase One { Kohonen Layer}

Step 0: Initialize the clusters weight vectors and the learning rate.

Step 1: Repeat from step 2-7 until the weight vectors converge.

Step 2: for each training input vector do steps 3-5.

Step 3: Set the input layer activation's to vector x.

Step 4: Find winning cluster unit using distance measure; call its index j.

Step 5: Update weight vector $v_j$ of unit j using:

$V_{ij}(new) = V_{ij}(old) + a(x_i.V_{ij}(old)$ 1=1,2,..,n)

Step 6: Reduce learning rate a.

Phase Two { Single Layer Linear Network}

Step 0: For each single layer linear net of a cluster do.

Step 1: Intialize weight vector w(randomly) and the learning rate a.

Step 2: set E=0 and K=0 (k is a counter for the number of associative examples to the current clusters net)

Step 3: k = k + 1

$$X = x_k$$
$$y = y_k$$
$$y' = \sum_{n=1}^{n} W_n X_n$$
$$e = y - y'$$
$$Wj = Wj + a \frac{eX_j}{\|x\|^2}$$
$$y' = \sum_{n=1}^{n} W_M X_M$$
$$E = E + abc(y - y')$$

Step 4: if $k<m$ then go to 3

Step 5: if $E > E_0$ then go to 2

where

E : the absolute error of current cluster

$E_0$: the previous absolute error of the current cluster.

$W_j$:the jth weight of the processing element.

y': the actual output of the cluster.

y: the desired output

X: the input vector.

a: the learning rate

M: the number of associated examples with the current cluster net.

**Table 1: Performance and comparison of existing and proposed technique for image size 256 X 256**

| Image size 256 x 256 Cameraman | Wavelet - MFOCPN | | |
|---|---|---|---|
| | Cluster 32 | Cluster 64 | Cluster 128 |
| PSNR | 24.4335 | 24.5442 | 24.5471 |
| MSE | 234.2800 | 228.3801 | 228.2283 |

| Image size 256 x 256 Cameraman | Wavelet - MSLLFOCPN | | |
|---|---|---|---|
| | Cluster 32 | Cluster 64 | Cluster 128 |
| PSNR | 27.9068 | 28.2028 | 28.2233 |
| MSE | 105.294 | 98.356 | 97.8917 |

**Table 2: Performance and comparison of existing and proposed technique for image size 512 X 512**

| Image size 512 x 512 Cameraman | Wavelet - MFOCPN | | |
|---|---|---|---|
| | Cluster 32 | Cluster 64 | Cluster 128 |
| PSNR | 24.2335 | 24.3541 | 24.4252 |
| MSE | 234.2800 | 234.3801 | 234.7253 |

| Image size 512 x 512 Cameraman | Wavelet - MSLLFOCPN | | |
|---|---|---|---|
| | Cluster 32 | Cluster 64 | Cluster 128 |
| PSNR | 30.9335 | 31.5442 | 31.8199 |
| MSE | 42.2800 | 42.3801 | 42.7655 |

Subjective visual results for the existing and proposed techniques

| | |
|---|---|
|  |  |
| a) Wavelet-MFOCPN 256 x 256 with 128 cluster | b) Wavelet-MSLLFOCPN 256 x 256 with 128 cluster |
|  |  |
| c) Wavelet-MFOCPN 512 x 512 with 128 cluster | d) Wavelet-MSLLFOCPN 512 x 512 with 128 cluster |