Abstract—With the advances in wireless communications and embedded systems, efficient storage and transmission of images and video over limited bandwidth is required. Novel image compression techniques need to be investigated; an artificial neural networks subsampling image compression method is presented using the Al-Alaoui backpropagation algorithm is used [1-5]. The Al-Alaoui algorithm is a weighted mean-square-error (MSE) approach to pattern recognition. It employs cloning of the erroneously classified samples to increase the population of their corresponding classes. Using the Al-Alaoui backpropagation, obtained simulation results show a faster convergence rate, zero misclassified pixels and an improvement in PSNR around 2 dB.

I. INTRODUCTION

Most image compression techniques are based on either statistical approaches or applying transforms such as DCT and wavelet transform. JPEG standard is based on DPCM for DC coefficients and on DCT for AC coefficient while the new JPEG2000 standard is based on wavelet transform [6-8]. Though we are getting higher compression ratios and better quality, the major drawback is complexity. These algorithms are most of the time difficult to implement on embedded systems since they require powerful microprocessors, thus, increasing cost and power consumption.

Alternatives were proposed based on artificial neural networks (ANN). ANN are suitable for image compression due to their massively parallel and distributed architecture. Multilayer perceptrons were used as nonlinear predictor replacing the known ARM linear predictor [9].

Also ANN were used in transform coding to solve problems associated with the calculation of the basis vectors through eigendecomposition of the covariance estimate. These approaches require less storage overhead and can be more computationally efficient [10].

Dimitras and Kossentini [11] introduced a fast and high performance image subsampling method using backpropagation algorithm and showed that the proposed method outperforms the standard lowpass filtering and subsampling method. This paper extends the innovative work performed in [11] by choosing a different pattern matching technique to select the desired output values during the supervised training stage. In addition, the Al-Alaoui backpropagation (ALBP) will be implemented instead of the standard backpropagation approach.

This paper is organized as follows. Section II provides an overview of the Al-Alaoui backpropagation algorithm. The proposed compression algorithm is presented in Section III while Section IV presents the simulation results. Finally, Section V draws a conclusion.

II. AL-ALAOUI BACKPROPAGATION ALGORITHM

For the multilayer neural networks using the backpropagation algorithm, convergence is usually reached for many of the classification problems and thus no improvement in the classification is required. The algorithm, however, can be adapted to speed up the convergence of the back-propagation algorithm by reintroducing, cloning, the erroneously classified samples [12].

The Al-Alaoui algorithm for neural networks is described as follows (Figure 1):

1. Initialize parameters and set desired misclassification error rate.
2. Perform backpropagation for a predefined number of epochs.
3. If the chosen maximum number of epochs is reached then stop otherwise continue to step 4.
4. Test original input vector before cloning and determine the misclassification percentage error.
5. If the desired rate is obtained stop otherwise continue to step 6.
6. Clone misclassified samples in original training set and append them to the input array. Go back to step 2.
The algorithm reduces the number of misclassifications by cloning the erroneously classified samples and adding them to the training set. This approach gives more weight to samples close to the classification boundaries by cloning them upon being erroneously classified. For multi-layer networks, the back-propagation method, irrespective of learning rate adaptability and the use of momentum, is applied for a selected number of epochs, each consisting of the whole input set of training samples. The input set is then tested and the clones of the samples that are misclassified are added to the training set to yield a new input set for the next group of epochs. The process continues until all samples are correctly classified, or until the number of misclassifications has dropped to some desired level, or until the number of prespecified iterations has been reached, keeping the best obtained solution. This approach will yield a better approximation to the optimum Bayes classifier. For detailed algorithm description refer to [1-5].

III. SUBSAMPLING IMAGE COMPRESSION USING FEEDFORWARD NEURAL NETWORKS

Figure 2 shows the block diagram of the conventional as well as the proposed method in [11]; instead of performing the conventional subsampling using a lowpass filter and downsample the rows and columns, the image is divided into 2x2 blocks and then converted to a column of four pixels to be inputted to the ANN. The feedforward architecture has only one neuron in the output layer and thus a compression of ratio 4:1 is obtained. The used technique to extract the output training set is described as follows (applied to every 2x2 block):

- Compute the median of all possible spatial three-pixel location of the 2x2 block. For each possibility, subtract the result from the gray level of the 4th pixel and square the result (n1 and n2 are the horizontal and vertical direction respectively):
  - \[ Q_1 = (x_{n1,n2} - \text{median}(x_{n1+1,n2-1}, x_{n1-1,n2+1}, x_{n1-1,n2-1}, x_{n1+1,n2+1}))^2 \]
  - \[ Q_2 = (x_{n1+1,n2} - \text{median}(x_{n1,n2+1}, x_{n1-1,n2+1}, x_{n1+1,n2+1}, x_{n1+1,n2+1}))^2 \]
  - \[ Q_3 = (x_{n1,n2+1} - \text{median}(x_{n1,n2-1}, x_{n1,n2-1}, x_{n1+1,n2+1}, x_{n1+1,n2+1}))^2 \]
  - \[ Q_4 = (x_{n1-1,n2-1} - \text{median}(x_{n1-1,n2-1}, x_{n1-1,n2-1}, x_{n1-1,n2-1}, x_{n1-1,n2-1}))^2 \]

Figure 2. Block Diagrams of (a) Conventional Subsampling System (b) ANN Image Subsampling System.
• Get the minimum of the above four obtained values:
  \( \min\{Q1,Q2,Q3,Q4\} \).
• The index of the minimal value will be used where the
desired output (target) for the corresponding block is
\( x(\text{index}) \), \( x \) being the input to the ANN. For example if
\( Q1 \) is the minimum, the desired output is \( x_{n1,n2} \).

Simulations results in [11] showed the superiority of this
approach over the conventional subsampling technique.
In this paper we attempt to extend the results by further
enhancing the compression image quality by increasing the
PSNR. The modifications are listed below:
1. The input and output of the ANN are normalized between
0 and 1 giving a higher dynamical range.
2. The ANN is modified from 4-2-1 to 4-9-1, MATLAB
simulation showed that the sum squared error is reduced
when using nine neurons in the hidden layer.
3. The Al-Alaoui backpropagation algorithm is used instead
of standard backpropagation. Note that the ALBP is
designed for classification problems; the subsampling image
compression problem can be transformed into a
classification one; for each input vector, the obtained output
is compared to the desired one. If the difference is less than
a certain threshold (i.e \( T = 5 \)) then the input is considered to
be correctly classified and, thus, will not be cloned.
4. Sort \( \{x_{n1,n2},x_{n1-1,n2},x_{n1,n2-1},x_{n1-1,n2-1}\} \) in ascending
order as \( \{a,b,c,d\} \). The desired output of the training set will
be \( (b+c)/2 \) which is much closer to the original 2\times2 block
which is perceived as a single dot when viewed from a
distance.

The next section presents the results obtained using the
method proposed in [11] and the one proposed in this paper.

IV. SIMULATION RESULTS

Simulations were conducted on Pentium IV, 3.0 Ghz CPU
with 512 MB DDRAM memory running windows XP
operating system. A 4 – 9 – 1 feedforward ANN
architecture is used with a learning rate of 0.01 and a
momentum constant equals to 0.95. MATLAB were used for
simulation along with Neural Networks Toolbox and the
Levenberg–Marquardt for both standard backpropagation
algorithm (designated as LMBP) and the modified
backpropagation (designated as ALBP). Batch processing is
used for training; simulation results revealed that the
reduction in the sum squared error is minimal after 500
epochs. The cloning rate for the ALBP is 100 epochs.
The objective quality metric used to compare results of
[11] and the one proposed is the peak signal to noise ratio
(PSNR).

The 256x256 ‘lena’ image were used for training and the
512x512 ‘fishing boat’ image for testing. Table 1 shows the
number of misclassified pixels for both the LMBP and the
ALBP for the same training set and the same initial weights
and biases. Note that the number of misclassified pixels is
reduced to zero after 300 epochs thus cutting the training
time; the ALBP has a faster convergence rate and no
misclassified pixels. Figure 3 shows the images obtained for
the method adopted in [11] and the proposed one with the
modifications listed in section III. Note the increase in
PSNR by 2 dB and the reduction in artifacts effects. Since
the testing input image size is 512x512, the resultant
compressed image will be 256x256; bicubic interpolation is
used to restore the original size and to measure the PSNR.

Table 1. Comparison of LMBP and ALBP for the ‘lena’
image.

<table>
<thead>
<tr>
<th></th>
<th>LMBP</th>
<th>ALBP</th>
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<tr>
<td>Epoch number</td>
<td>Misclassification (pixels)</td>
<td>Elapsed time (sec)</td>
</tr>
<tr>
<td>0/500</td>
<td>15649/16384</td>
<td>0</td>
</tr>
<tr>
<td>100</td>
<td>376/16384</td>
<td>42.59</td>
</tr>
<tr>
<td>300</td>
<td>59/16384</td>
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<td>500</td>
<td>56/16384</td>
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<tr>
<td>0</td>
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</tr>
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<td>26/16384</td>
<td>41.98</td>
</tr>
<tr>
<td>300</td>
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</table>
Figure 3. (a) Original Image, (b) Restored Image using LMBP and training set proposed in [11], (c) Restored Image using ALBP and method proposed in this paper.