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ORIGINAL PAPER

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Image compression and reconstruction using pi$_t$-sigma neural networks

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Abstract A high-order feedforward neural architecture, called pi$_t$-sigma ($\pi_t\sigma$) neural network, is proposed for lossy digital image compression and reconstruction problems. The $\pi_t\sigma$ network architecture is composed of an input layer, a single hidden layer, and an output layer. The hidden layer is composed of classical additive neurons, whereas the output layer is composed of translated multiplicative neurons (π_t-neurons). A two-stage learning algorithm is proposed to adjust the parameters of the $\pi_t\sigma$ network: first, a genetic algorithm (GA) is used to avoid premature convergence to poor local minima; in the second stage, a conjugate gradient method is used to fine-tune the solution found by GA. Experiments using the Standard Image Database and infrared satellite images show that the proposed $\pi_t\sigma$ network performs better than classical multilayer perceptron, improving the reconstruction precision (measured by the mean squared error) in about 56%, on average.

Keywords Neural networks · Image compression · Multiplicative neurons · High-order neural networks · Genetic algorithm

1 Introduction

The expansion of multimedia information processing systems, associated to physical limitations on bandwidth of transmission lines and limited capacity of storage devices, resulted in an increasing interest on data compression technologies, both in industry and in academia. And, since high quality digital images are one of the most demanding (in terms of required storage space) elements in a multimedia information system, specific research on digital image compression methods is of great interest. Methods such as Discrete Cosine Transform (DCT) and wavelet transform have been widely applied for lossy image compression and reconstruction.

Because of its nonlinear processing capabilities and universal approximation characteristic, classical Multilayer Perceptron (MLP) neural networks and some of its variations have already been applied in lossy image compression problems [10,13]. On the other hand, applications of neural network architectures employing multiplicative neurons in image compression and reconstruction problems have not been investigated yet. These multiplicative networks may present better approximation capability and faster learning times than the classical MLP (which employ additive neurons only), because of its capability of processing higher-order information from training data [3,9,14]. Therefore, multiplicative networks have higher nonlinear processing abilities than classical neural network models. Because digital images are highly nonlinear mappings, neural networks with expanded nonlinear processing abilities are needed to realize better compression using the smallest amount possible of computational resources.

Therefore, a multiplicative neural network, called pi$_t$-sigma ($\pi_t\sigma$) network, is proposed for image compression and reconstruction problems. The $\pi_t\sigma$ network is a feedforward network composed of an input layer, a hidden layer of additive neurons, and an output layer composed of translated multiplicative neurons (π_t-neurons) [7]. It has been shown that neural networks using π_t-neurons and trained by supervised learning techniques may present better performance than classical neural networks in function approximation [7] and pattern classification problems [5]. The $\pi_t\sigma$ network is trained using a supervised learning algorithm, composed of two stages: (1) a genetic algorithm (GA) is used to avoid

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local minima in the error surface; and (2) the scaled conjugate gradient (SCG) is applied to fine-tune the solution found by GA.

To assess the efficacy of the proposed method, two image compression/reconstruction experiments are performed. In the first one, the ability of $\pi_t\sigma$ network to produce high quality reconstructed images is investigated using the Standard Image Database (SIDBA). In this experiment, images compressed and reconstructed using $\pi_t\sigma$ network have, on average, mean squared error (MSE) 20% lower than those produced by classical MLP. In the second experiment, the generalization ability of $\pi_t\sigma$ network is evaluated, using infrared images taken by a Geostationary Operational Environmental Satellite (GOES). The MSE of images compressed and reconstructed by the proposed approach is about 20% lower than that of classical MLP.

In Sect. 2, the main approaches for neural image compression are reviewed. Sect. 3 presents the π_t-neuron model. Sect. 4 describes the $\pi_t\sigma$-network and its learning algorithm. Sect. 5 presents the results obtained in compression/reconstruction experiments using SIDBA and infrared satellite images.

2 Feedforward neural networks for image compression

There are many possible approaches for image compression using neural networks proposed in the literature [8]. Among these approaches, lossy image compression using feedforward neural networks trained by supervised learning techniques have produced promising results [10,13]. These methods make use of the universal approximation capability of such neural networks to produce high quality reconstructed images, which are approximations of the original image.

The procedure adopted for image compression and reconstruction using feedforward neural networks can be described as follows: initially, a digital image of size $M \times N$ pixels is divided in $m \cdot n$ blocks and these blocks are arranged in vectors $\mathbf{x}_{11}, \ldots, \mathbf{x}_{mn}$ of size $l = (M \cdot N)/(m \cdot n)$, as shown in Fig. 1. These $m \cdot n$ vectors of dimension l form the training data set for the neural network. Define $g : \Re^l \to \Re^l$, such that $g(\mathbf{x}_{ij}) = \mathbf{x}_{ij}$, $i = 1, \ldots, m$, $j = 1, \ldots, n$. The objective is to design a neural network able to approximate the mapping $g(\cdot)$, i.e., a neural network whose output $\mathbf{y}_{ij} (\in \Re^l)$ is given by

$$\mathbf{y}_{ij} \approx g(\mathbf{x}_{ij}) = \mathbf{x}_{ij}. \tag{1}$$

Figure 2 presents an overview of this learning procedure, where an MLP with a single hidden layer with K hidden neurons is used to approximate the mapping $g(\cdot)$. Note that, to reconstruct the original image, it is necessary to have the outputs of the hidden neurons for each training pattern and the weights between hidden neurons and output layer. In Fig. 2, there are $K \cdot l$ weights between hidden and output layers, and $K \cdot m \cdot n$ numerical values representing the hidden neuron outputs for each training pattern. Therefore, the compression rate ρ is defined by

$$\rho = \frac{K(m \cdot n + 1)}{M \cdot N}. \tag{2}$$

If $\rho < 1$, then a successful compression has been achieved. In the following, image compression methods employing the procedure presented above are briefly described.

Namphol et al. [13] propose a hierarchical neural network architecture for image compression, composed of three hidden layers, denoted combiner, compressor, and decombine. An image is divided in a number of sub-scenes and each of the sub-scenes is processed by a group of neurons in the combiner layer. The decombine layer is also divided in groups of neurons, each of them responsible for reconstructing a subscene from the signals generated by the compressor layer.

Ma and Khorasani [10] apply single hidden layer neural networks designed by a constructive learning algorithm to image compression. The learning algorithm is based on the cascade correlation algorithm [2]. Several experiments are performed to compare the constructive approach and fixed structure networks. Comparisons with baseline JPEG are also provided.

Although these two methods may perform better than existing image compression techniques, they employ neural networks composed of classical additive neurons only. It has been shown that neural architectures employing multiplicative neurons may outperform classical neural network architectures [3,9,14], both in terms of approximation accuracy and computational cost. This happens because multiplicative neurons can extract high-order information from learning data more efficiently than additive neurons.

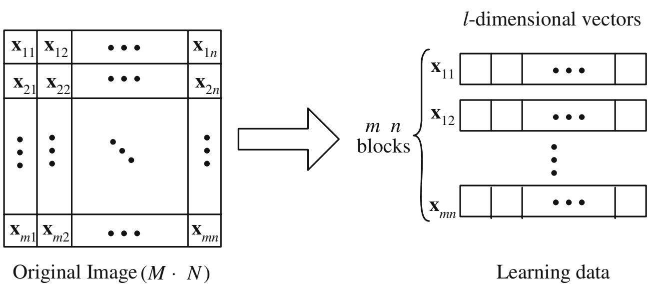

Fig. 1 Construction of neural network training data set. Here, $l = (M \cdot N)/(m \cdot n)$

3 Translated multiplicative neuron (π_t-neuron)

Artificial neuron models are usually composed of two blocks: an aggregation operator followed by an activation function [1]. The aggregation operator combines the neuron's inputs to produce a signal-called level of internal activation $v (\in \Re)$. The output $s (\in \Re)$ of the neuron is then given by $s = f(v)$, where $f : \Re \to \Re$ is the model's activation function.

Neuron models can be classified according to the type of aggregation operator and activation function employed [1]. When v is produced by an additive weighted composition of

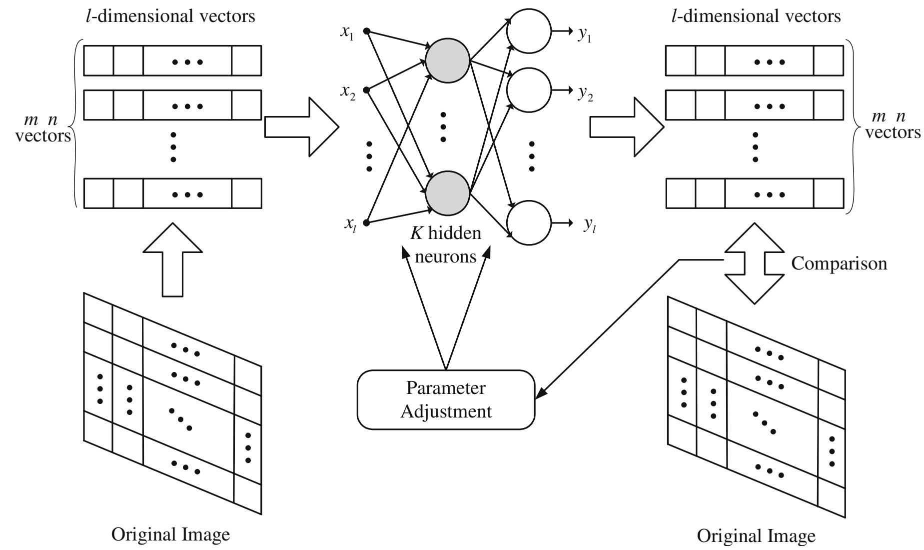

Fig. 2 Construction of neural network training data set

neuron's inputs, then the model is called additive neuron (or σ-neuron, for short), defined by

$$v = \sum_{i=1}^{m} w_i p_i, \tag{3}$$
$$s = f(v),$$

where $w_i (\in \Re), i = 1, \ldots, m$, are the weights (adjustable parameters) of the neuron and $p_i (\in \Re), i = 1, \ldots, m$ are the neuron's inputs. The model in (3) is the traditional McCulloch–Pitts neuron model.

The multiplicative neuron (π-neuron) [15] is defined by

$$v = \prod_{i=1}^{m} w_i p_i, \tag{4}$$
$$y = f(v),$$

where $w_i (\in \Re), i = 1, \ldots, m$, are the weights of the model. Note that the model in (4) has two properties that may limit its applicability in complex problems [7]: (1) it has an excessive number of parameters and (2) decision surfaces generated by this model are always centered in the origin of the neuron's input space $\Re^m$.

To expand the capabilities of the π-neuron model, the translated multiplicative neuron (π_t-neuron) has been proposed [7]. The π_t-neuron model is defined by

$$v = b \prod_{i=1}^{m} (p_i - t_i), \tag{5}$$
$$s = f(v),$$

where the parameters $t_i (\in \Re), i = 1, \ldots, m$, represent the coordinates of the center of the decision surface generated by the model, and $b (\in \Re)$ is a scaling factor. The π_t-neuron model has two advantages, when compared to the traditional multiplicative neuron: (1) it has a meaningful set of adjustable parameters and (2) the decision surfaces generated by this model can be placed in any point of its input space.

The π_t-neuron model has been tested in some supervised learning problems, including nonlinear regression [7] and pattern classification [5]. In most of these problems, neural networks employing π_t-neurons could achieve better performance than classical neural network models. It has also been shown that a single π_t-neuron can solve the N-bit parity problem [6]. These results confirm that the π_t-neuron has expanded information processing capabilities when compared to the classical additive neuron model. These capabilities seem to be more evident when the data to be approximated has a high degree of nonlinearity.

Because typical digital images are mappings containing high degree of nonlinearity, a neural network should have improved nonlinear processing capabilities to realize the mapping in (1) using the smallest amount possible of computational resources (i.e., number of hidden neurons and connection weights). Since networks using π_t-neurons have expanded nonlinear processing abilities, a neural network architecture containing π_t-neurons as processing elements is proposed for digital image compression and reconstruction problems. The proposed network is described in detail in Sect. 4.

4 The pi$_t$-sigma ($\pi_t\sigma$) neural network

The pi$_t$-sigma ($\pi_t\sigma$) neural network used for image compression and reconstruction is depicted in Fig. 3. The $\pi_t\sigma$ is a feedforward neural network, composed of an input layer with l nodes, a hidden layer of $K \sigma$-neurons, and an output layer of $l \pi_t$-neurons. The network's output $y_p (\in \Re), p = 1, \ldots, l$, is given by

$$y_p = b_p \prod_{i=1}^{K} \left(f\left(\sum_{j=1}^{l} (w_{ij} x_j - w_{0j}) \right) - t_{pi} \right), \tag{6}$$

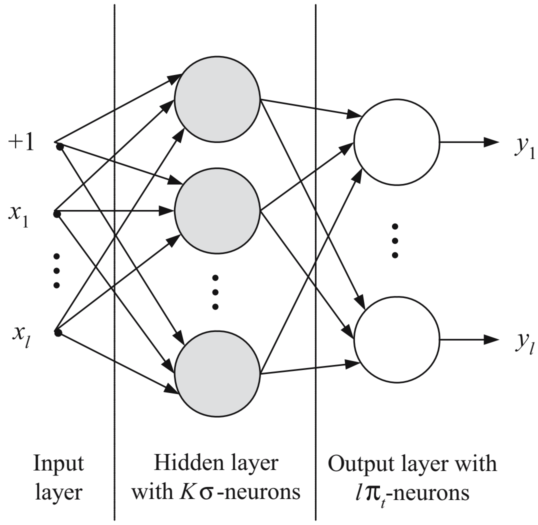

Fig. 3 The pi$_t$-sigma ($\pi_t\sigma$) neural network architecture

where $w_{ij}(\in \Re)$, $i = 1, \ldots, K$, $j = 1, \ldots, l$, is the weight connecting the input x_j to the hidden neuron i and $w_{0j}(\in \Re)$ is the weight connecting the bias term $x_0 = +1$ to the ith hidden neuron. The parameters $b_p(\in \Re)$ and $t_{pi}(\in \Re)$, $p = 1, \ldots, l$, $i = 1, \ldots, K$, are the parameters of the π_t-neurons in the output layer of the network.

The σ-neurons in the hidden layer work as a feature extractor, thus reducing the dimensionality of the input space. Because of the multiplicative characteristic of the π_t-neuron model, the output layer of the $\pi_t\sigma$ network is able to (indirectly) detect higher-order correlations in the learning data. In other words, it has expanded information processing capabilities in comparison with the classical MLP model. Therefore, the $\pi_t\sigma$ network has the potential to better describe the true input–output mapping using a smaller number of hidden neurons.

The $\pi_t\sigma$ network can be considered as an extension of the pi-sigma neural architecture [3], which employs the π-neuron model defined in (4) in its output layer. Since the original pi-sigma neural architecture has the universal approximation property, it is clear that the $\pi_t\sigma$ network is also a universal approximator.

4.1 Learning algorithm of $\pi_t\sigma$ neural network

Although there are numerous heuristics and strategies to initialize classical MLP networks [4, Chap. 4], strategies to initialize the weights of networks containing of π_t-neurons have not been established yet. During the initial experiments stage, the SCG algorithm [12] was used to train $\pi_t\sigma$ networks, but convergence to poor local optima was observed very often.

To avoid the premature convergence problem, a two-stage learning procedure is adopted. First, a GA is used to find a suboptimal solution. After the termination of the genetic search, the SCG is used to fine-tune the solution found by GA.

The standard GA [11] is employed and its main characteristics are as follows.

- Codification: a chromosome is a floating-point vector **p** of dimension $(l + 1)K + (K + 1)l$, where each element of the vector represents an adjustable parameter (w_{ij}, b_p, and t_{pi}) of the network described in (6) and depicted in Fig. 3.
- Fitnes function: each chromosome is evaluated by

  $$fit(\mathbf{p}) = \frac{1}{MSE(\mathbf{p})},$$

  where $MSE(\mathbf{p})$ is the mean squared error of the network codified by **p**, defined as

  $$MSE(\mathbf{p}) = \frac{1}{2m \cdot n} \sum_{i=1}^{m \cdot n} \sum_{j=1}^{l} \left(y_j^{(i)} - x_j^{(i)} \right)^2, \quad (7)$$

  where $y_j^{(i)}$ is the j-th network output for i-th training pattern, and $x_j^{(i)}$ is its corresponding target value.
- Selection operator: chromosomes are selected for the next generation using the roulette wheel operator, which assigns selection probabilities proportional to the fitness of the individual.
- Crossover operator: uniform crossover, where the elements of two parent chromosomes are exchanged with a certain proability.
- Mutation operator: gaussian mutation, where an element p_i of a chromosome selected for mutation is modified according to

  $$p_i = p_i + N(0, 1),$$

  where $N(0, 1)$ is a gaussian random variable with 0 mean and standard deviation 1.

The SCG algorithm is chosen because it does not require any line search procedure and does not have any critical user-defined parameter. Details about SCG can be found in [12].

To confirm the efficacy of the proposed learning scheme, a simple compression/reconstruction experiment is performed using the benchmark image lenna. In this experiment, the performance of a $\pi_t\sigma$ neural network with five hidden neurons trained using SCG only is compared to a $\pi_t\sigma$ network trained by the proposed GA+SCG learning algorithm. The parameters of the GA are as follows:

- population size: 150;
- maximum number of generations: 10,000;
- crossover probability: 0.8;
- mutation probability: 0.0001.

For the SCG, the maximum number of epochs is set to 10,000, whereas the stop criterion is defined as norm of error gradient smaller than 0.001.

Table 1 Mean squared error (MSE) for Standard Image Database (SIDBA) reconstructed images

Image	Number of hidden neurons							
	4		5		6		7	
	MLP	$\pi_t\sigma$	MLP	$\pi_t\sigma$	MLP	$\pi_t\sigma$	MLP	$\pi_t\sigma$
Airplane	0.0478	0.0185	0.0285	0.0141	0.0461	0.0111	0.0353	0.0095
Barbara	0.0741	0.0222	0.0337	0.0156	0.0308	0.0122	0.0335	0.0082
Boat	0.0189	0.0089	0.0175	0.0054	0.0170	0.0045	0.0220	0.0043
Bridge	0.0830	0.0412	0.0606	0.0322	0.0494	0.0271	0.0370	0.0243
Building	0.0335	0.0135	0.0427	0.0103	0.0255	0.0066	0.0245	0.0065
Cameraman	0.0397	0.0232	0.0336	0.0188	0.0401	0.0147	0.0418	0.0145
Girl	0.0214	0.0072	0.0164	0.0064	0.0164	0.0049	0.0107	0.0043
Lax	0.0732	0.0434	0.0494	0.0333	0.0543	0.0285	0.0641	0.0243
Lenna	0.0250	0.0111	0.0201	0.0091	0.0285	0.0081	0.0170	0.0063
Lighthouse	0.0688	0.0322	0.0457	0.0294	0.0326	0.0204	0.0474	0.0165
Text	0.0302	0.0294	0.0305	0.0204	0.0274	0.0178	0.0299	0.0151
Woman	0.0268	0.0116	0.0390	0.0085	0.0208	0.0068	0.0237	0.0061

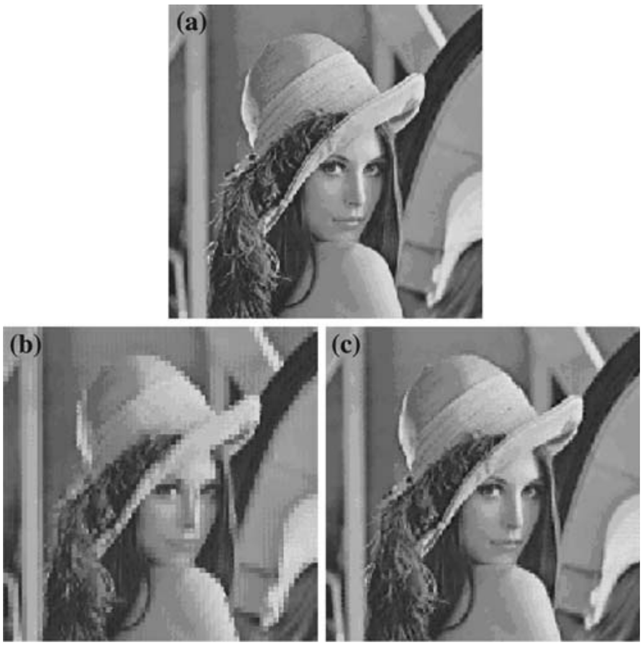

Fig. 4 Comparison of proposed learning algorithm: **a** Original image; **b** compressed and reconstructed with SCG only; **c** Compressed and reconstructed with GA+SCG

The images compressed and reconstructed by the compared learning algorithms are shown in Fig. 4b and c. The MSE of the image obtained using SCG only is 0.027, whereas the MSE of the image obtained by GA+SCG is 0.007. Therefore, the efficacy of the proposed GA+SCG learning algorithm is confirmed.

5 Compression and reconstruction of the SIDBA and infrared satellite images

To confirm the validity of the proposed approach, two experiments are performed. In the first experiment, images from the SIDBA are employed to evaluate the approximation capability of the proposed $\pi_t\sigma$ neural network. In the second experiment, the generalization capability of $\pi_t\sigma$ neural network is investigated using infrared images taken by a Geostationary Synchronous Satellite. In both experiments, the performance of $\pi_t\sigma$ network is compared to that of classical multilayer perceptrons.

5.1 Compression and reconstruction of the SIDBA

The SIDBA is composed of 12 grayscale images, some of them widely used to test the performance of image processing algorithms. The images of SIDBA are shown in Fig. 5. All the images are of size 256×256, i.e., $N = M = 256$. To construct the training data set for the neural networks, all the images are divided in blocks of size 4×4, i.e., $n = m = 4$. Therefore, the dimension of the input space is $l = 16$ and there are 16,556 training patterns. The images of the SIDBA can be downloaded from http://www.sp.ee.musashi-tech.ac.jp/app.html.

Two neural architectures are compared:

(1) Multilayer perceptron with sigmoidal activation function in the hidden neurons and linear activation function in the output neuron. The MLP is trained using the SCG algorithm. The maximum number of epochs is set to 10,000 and the stop criterion is norm of error gradient smaller than 0.001.
(2) Pi$_t$-sigma neural network, with logistic activation function in the hidden neurons and linear activation function in the output neurons. The parameters for the GA are as follows:
   - population size: 150;
   - maximum number of generations: 10,000;
   - crossover probability: 0.8;
   - mutation probability: 0.0001.

Fig. 5 The Standard Image Database (SIDBA): **a** airplane; **b** barbara; **c** boat; **d** bridge; **e** building; **f** cameraman; **g** girl; **h** lax; **i** lenna; **j** lighthouse; **k** text; **l** woman

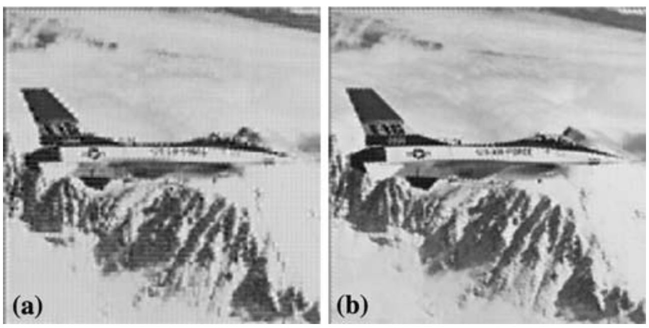

Fig. 6 Airplane image compressed and reconstructed by: **a** MLP; **b** $\pi_t\sigma$ network. Both networks have five hidden neurons

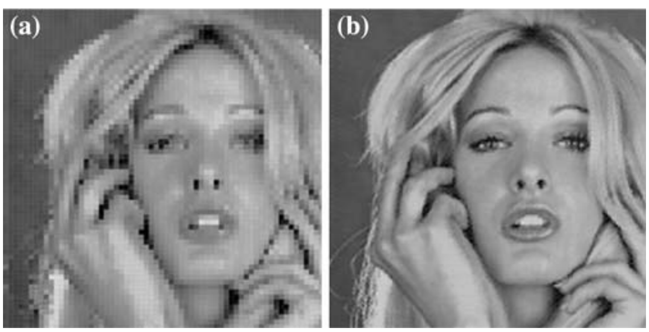

Fig. 7 Woman image compressed and reconstructed by: **a** MLP; **b** $\pi_t\sigma$ network. Both networks have five hidden neurons

For the SCG, the maximum number of epochs is 10,000, whereas the stop criterion is norm of error gradient smaller than 0.001.

For each neural architecture, the number of hidden neurons is varied between four and seven.

Table 1 shows the mean squared error of the images compressed and reconstructed by MLP and $\pi_t\sigma$ networks. For all the cases the proposed $\pi_t\sigma$ network obtained better

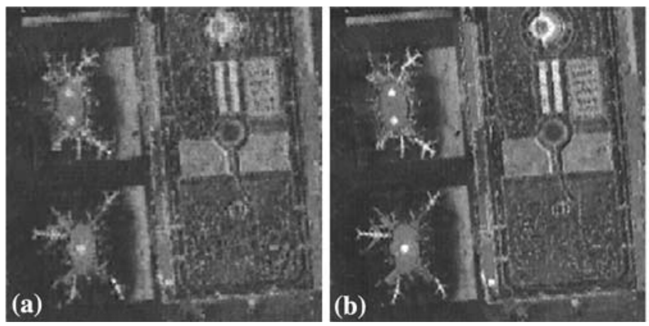

Fig. 8 Lax image compressed and reconstructed by: **a** MLP; **b** $\pi_t\sigma$ network. Both networks have five hidden neurons

performance than traditional MLP. Figures 6, 7, and 8 show examples of images compressed and reconstructed by the two neural networks considered. From these figures, it is possible to notice the higher quality of the images reconstructed using the proposed method.

From the results it is confirmed that, using the same number of hidden neurons, the proposed $\pi_t\sigma$ network can achieve better performance than the classical MLP.

5.2 Compression and reconstruction of infrared satellite images

To evaluate the generalization capability of the proposed $\pi_t\sigma$ neural network, a set of infrared images taken by a GOES orbiting Japan is used. The images generated by this satellite are grayscale, of size 800 × 800, i.e., $M = N = 800$. Six images taken in January 2000 are chosen for this experiment; one image is used to train the neural networks considered and the other five images are used to test their generalization ability. These images are shown in Fig. 9.

To construct the training data set, the training image (Fig. 9a) is divided in blocks of size 8×8, i.e., $m = n = 8$. Thus,

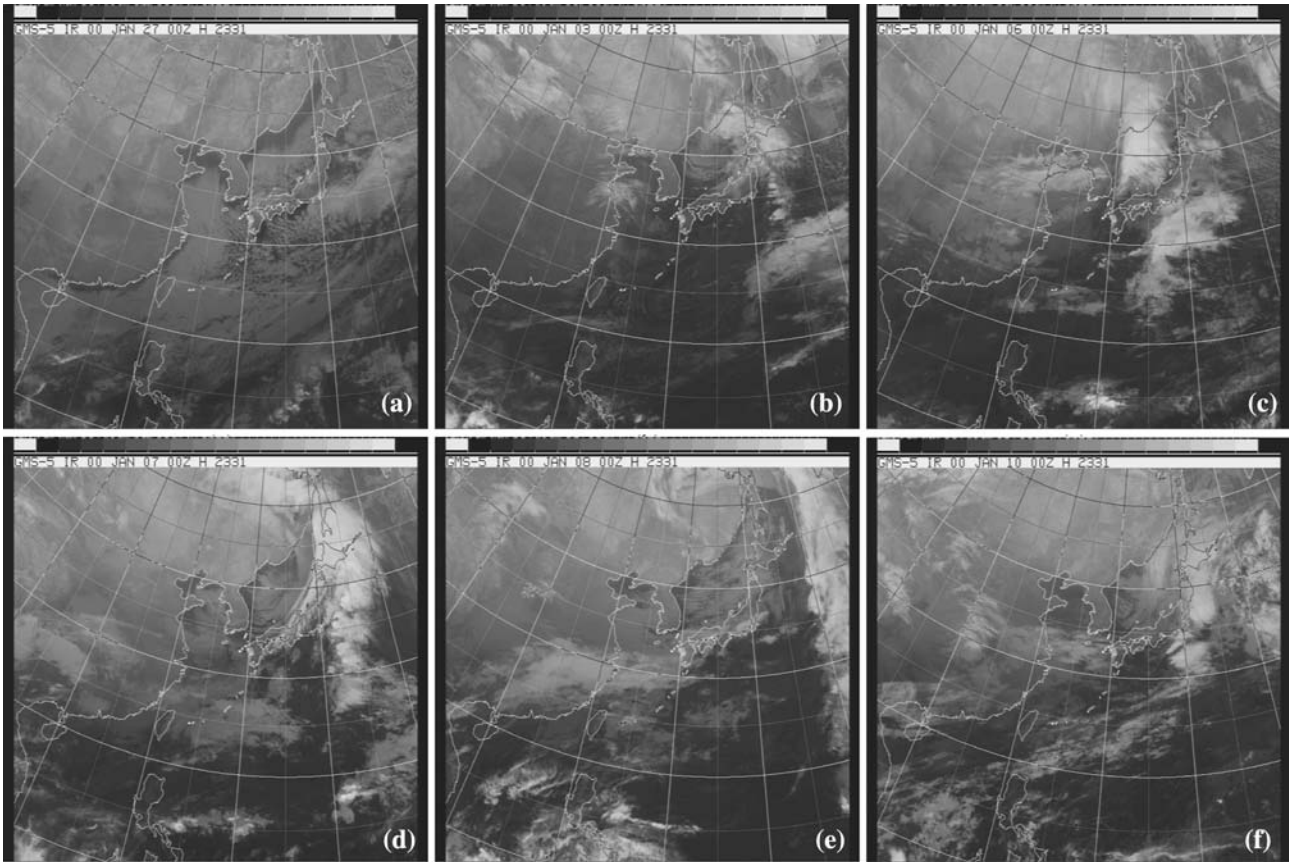

Fig. 9 The infrared Geostationary Operational Environmental Satellite (GOES) images: **a** 00012709.h; **b** 00010309.h; **c** 00010609.h; **d** 00010709.h; **e** 00010809.h; **f** 00011009.h. The image (**a**) is used for training, whereas the images (**b**)–(**f**) are used for testing

the training data has dimension $l = 64$ and there are 10,000 training instances.

Two neural architectures are compared:

(1) Multilayer perceptron with eight hidden neurons using logistic activation function and output neurons using linear activation function. The MLP is trained using the SCG algorithm. The maximum number of epochs is set to 10,000 and the stop criterion is norm of error gradient smaller than 0.001.
(2) Pi$_t$-sigma neural network, with logistic activation function in the hidden neurons and linear activation function in the output neurons. The parameters for the GA are as follows:
   - population size: 150;
   - maximum number of generations: 10,000;
   - crossover probability: 0.4;
   - mutation probability: 0.0001.

   For the SCG step, the maximum number of epochs is 10,000, whereas the stop criterion is norm of error gradient smaller than 0.001.

Table 2 compares the results obtained by MLP and $\pi_t\sigma$ neural networks. The performance measured used is the MSE, defined in (7). In this experiment, $\pi_t\sigma$ neural network can again achieve better performance than classical MLP, in all the images considered. Figure 10 shows the images compressed and reconstructed by MLP, whereas Fig. 11 shows the images obtained using the proposed $\pi_t\sigma$ neural network. Again, it is possible by visual inspection to notice that the images reconstructed by the proposed method are of higher quality than those reconstructed by MLP.

The results of this experiments show that, besides having better approximation properties, $\pi_t\sigma$ network has also better generalization capability than the traditional MLP.

Table 2 Mean squared error of Geostationary Operational Environmental Satellite (GOES)-reconstructed images. Both networks have eight hidden neurons. The image 00012709.h is the training image

Image	MLP	$\pi_t\sigma$ network
00012709.h	0.16976	0.07611
00010309.h	0.18273	0.08387
00010609.h	0.18585	0.08502
00010709.h	0.18570	0.08415
00010809.h	0.18656	0.08261
00011009.h	0.18705	0.08399

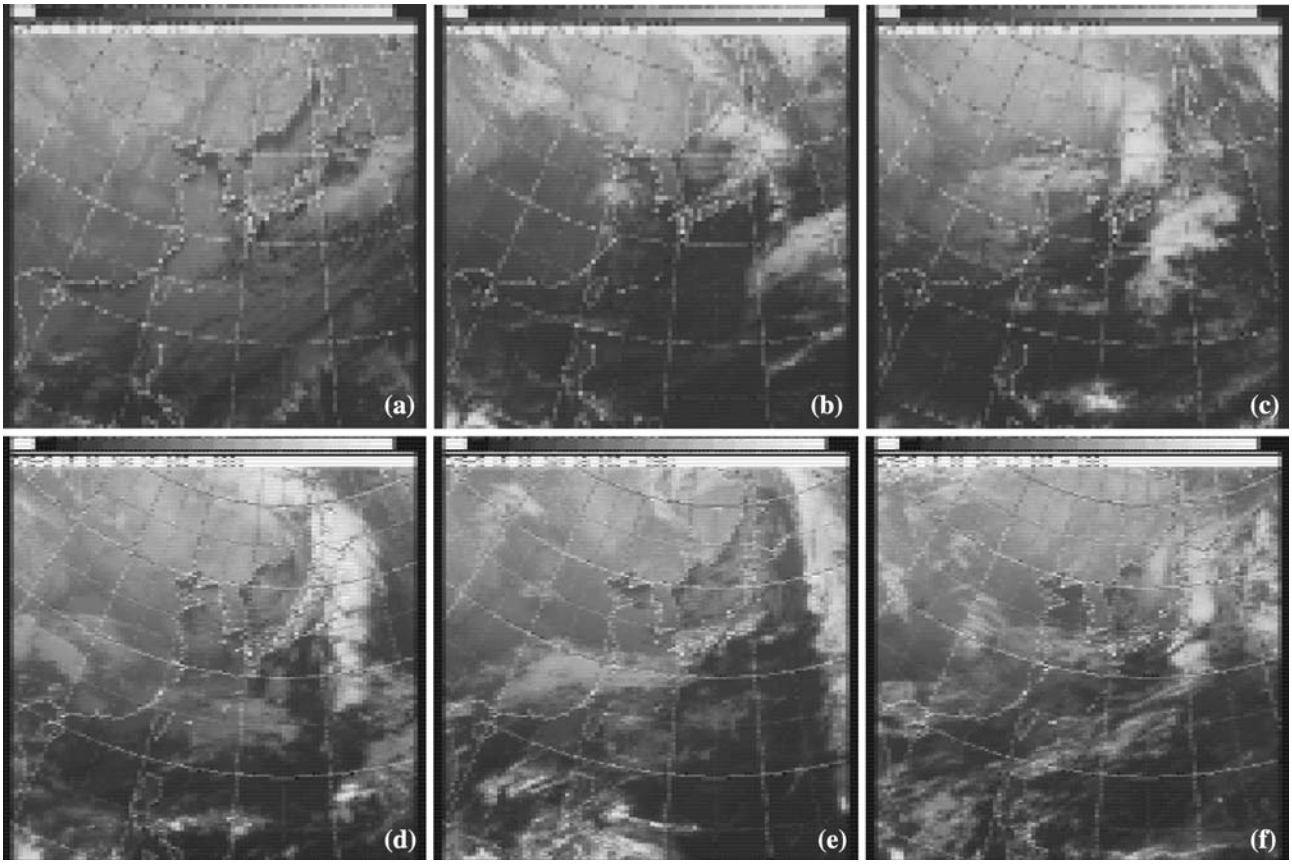

Fig. 10 The infrared GOES images compressed and reconstructed by Multilayer Perceptrons (MLP). The image (**a**) is the training image

6 Conclusions

A neural architecture called $\pi_t\sigma$ neural network is proposed for digital image compression and reconstruction. The $\pi_t\sigma$ neural network is composed of an input layer, a hidden layer of additive neurons, and an output layer of translated multiplicative neurons (π_t-neurons) [7]. The multiplicative characteristic of π_t-neuron model enables the proposed $\pi_t\sigma$ network to extract (indirectly) high-order information from the training image data.

The learning algorithm of $\pi_t\sigma$ network is composed of two stages. First, a floating-point GA is used to avoid local minima in the network's error surface. After the evolutionary process, the SCG [12] is used to fine-tune the solution found by GA. Experiment results show that the combined GA+SCG learning algorithm produces reconstructed images with MSE about 20% lower than that produced using SCG only.

To evaluate the performance of $\pi_t\sigma$ network in image compression and reconstruction problems, two experiments are conducted. In the first experiment, images from the SIDBA are used to evaluate the approximation capability of $\pi_t\sigma$ network. The images compressed and reconstructed using the $\pi_t\sigma$ network have MSE about 57% lower than those obtained using classical MLP.

The generalization capability of $\pi_t\sigma$ network is evaluated using a set of infrared images obtained by a GOES. The set is composed of six images, where one is used for training and the remaining five are used for testing. The test images compressed and reconstructed by $\pi_t\sigma$ network have an MSE 55% smaller than those obtained by MLP.

The results confirm that the proposed $\pi_t\sigma$ network has better nonlinear approximation and generalization capabilities than the classical MLP architecture. They also confirm the suitability of the proposed network to digital image compression and reconstruction problems.

The proposed method requires long training times, due to the burden imposed by the GA and the big size of the training data. Since the proposed approach operates offline, this does not limit the applicability of the method. Furthermore, with the rapid advance of hardware computational power, it is certain that the proposed method will be running much faster in the near future. Another way to shorten the training time is to develop smart heuristics for initializing a $\pi_t\sigma$ network, thus eliminating the need for GA. This is certain a topic for future research.

Another future research direction is to investigate the performance of $\pi_t\sigma$ network in compression and reconstruction of color images. Furthermore, the applicability of $\pi_t\sigma$ network in video compression problems will also be considered.

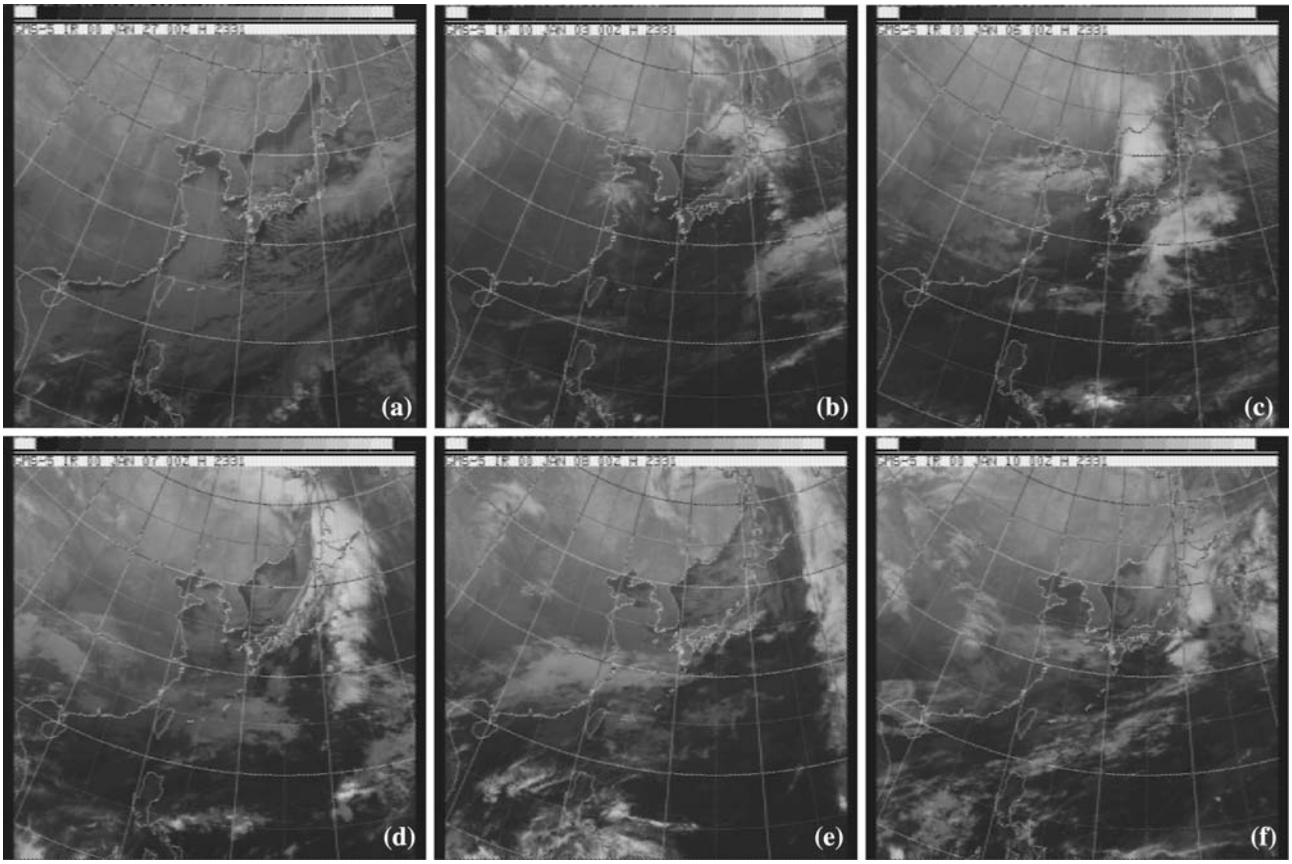

Fig. 11 The infrared GOES images compressed and reconstructed by $\pi_t\sigma$ network. The image (**a**) is the training image

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