نظام مركب يعتمد على الشبكات العصبية لضغط الصور المجسمة

A NEURAL NETWORK BASED HYBRID TECHNIQUE FOR DATA COMPRESSION Of STEREOPAIRS

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ملخص البحث:

يقدم البحث طريقة مركبه جديدة لضغط بيانات الصور المجسمة وتشتمل هذه الطريقة على ثلاث مراحل وهى مرحلة استخلاص التباين بين الصورتين اليمنى واليسرى ومرحلة الضاغط العصبى ثم مرحلة استخلاص الصورة المجسمه. وتتميز الطريقة المقترحة بوجود ثلاث مراحل لضغط البيانات وذلك عن طريق تحويل فورير الذى يستخدم لحساب التباين بين الصورتين وكذلك الضغط الأولى للبيانات قبل ادخالها للشبكة العصبية لتقليل عدد النيرونات الموجودة بطبقة الادخال. أما المرحلة الثانية لضغط البيانات فهى تتم بواسطة تصميم خاص للشبكة العصبية التى تقوم بضغط معاملات فورير التى يتم نقلها بعد ذلك من الطبقة المتوسطة (الضاغطة) الى المستقبل حيث يتم هناك استعادة معاملات فورير التى تم ادخالها لطبقة الادخال وذلك بتحويل فورير العكسى. المرحلة الثالثة لضغط بيانات الصور تتمثل فى نقل الاطار الخارجى للمناطق المختلفة فى الصورتين والتى يتم تحديدها باستخدام نموذج spin model . كما تمت دراسة تأثير المعاملات المختلفة التى تؤثر على اداء محلل التناظر بين الصورتين اليمنى واليسرى لاختيار افضل المعاملات لتعجيل عملية استخلاص مناطق التباين. هذه العملية تمكن من نقل الاجزاء المتباينة من الصورة اليسرى والتى تستخدم مع الصورة اليمنى المنضغطة لاستعادة الصورة المجسمة.

ABSTRACT:

This paper presents a new hybrid technique for efficient compression of stereopairs . The proposed technique encompasses three processing stages: a phase difference disparity interpreter, a neural network based image compressor / decompressor, and a stereopair reconstructor. The main advantage of the proposed technique lies in a threefold data compression. The first data compression stage is realized by using the Fast Fourier Transform (FFT) for computation of the disparity . Data compression is achieved by sending both the disparity and the compressed right image. The second data compression stage is achieved by clamping the significant part of the FFT coefficients of the right image to the input layer of the neural network for further data compression. This has the advantage of reducing the number of neurons in the input layer of the neural compressor. The third data compression stage is encompassed in the data compression of the previously FFT - compressed right image through the neural net data compressor. At the receiver, the disparity , the displaced subimage and the compressed right image are used to reconstruct the left image. Experiments are performed on both random and real stereopairs. The compression ratio of the neural network depends on the number of neurons in the hidden layer. The FFT of the input patterns is used to increase the compression ratio and to speed up the learning of the neural network. Correspondence analysis is performed using the spin model to obtain the dispairity map of the stereopair. System design parameters affecting the performace of the correspondence analyzer are studied to achieve optimal stereopair interpretation. This process makes it possible to transmit only the displaced regions in the left image . Another data compression step is achieved through the contour of the disparity map.

KEYWORDS:

Data compression, disparity, stereo vision, correspondence analysis, spin model, neural networks.

1. INTRODUCTION:

Data compression of stereopairs is a very important research field in computer vision and is essential for the efficient storage, transmission, and manipulation of digital images . Its applications include videophone images, weather maps, earth-resource pictures, medical images, and facsmile material. Because of the file sizes involved, transmitting images will always consume large amounts of bandwidth, and storing images will always require hefty resources. In videophones and high definition television (HDTV) the channel capacity is too small to allow transmission of all the information characterizing every pixel on the screen. Practical transmission schemes must therefore exploit the redundancy that naturally exists in most images, encoding the picture in a much smaller number of bits than the total required to describe it exactly. As stereopairs are used for more and more applications, it will become increasingly necessary to transmit and store them. If no data compression scheme is employed, twice as many bits are required to represent a stereopair as are required for a single image. The goal of this research is to exploit a hybrid architecture for effective image compression. The compressed image must then be decoded at the receiver into a full-sized image. There are three main groups of image data compression techniques : predictive coding , transform coding and hybrid coding as shown in Figure 1 . Image data compression is achieved by reducing inherent redundancies in images. Predictive coding (including the differential pulse code modulation (DPCM) uses the redundancy in the original picture space [1,2]. Transform coding uses a unitary (energy preserving) transformation from the image space into another one, with only a few generalized frequency samples retained. Progress in picture coding has led to high efficiency methods using local operators or contour texture description and run length coding (RLC).

There are many transforms for image coding [3,4] such as the Fast Fourier Transform (FFT), Fast Walsh-Hadamard Transform, Fast Haar transform (FHT), Fast Discrete Cosine Transform (FDCT), Fast Discrete Sine Transform (FDST) , Fast Slant Transform, Fast High Correlation Transform (FHCT) and Fast Karhunen Loeve Transform (KLT). All these transforms depend on the redundancy in image data for achieving data compression. Every transform has a certain energy packing capability and decorrelation efficieny. The KLT is the optimal transform concerning both criteria. But it requires the computation of its basic functions from the eigenvectors of the image under consideration.

Therefore it is a time consuming transform. The DCT is near optimal, and is much faster than the KLT. The FFT performance is not much inferior to that of the DCT, however it has the disadvantage of performing complex computations, therefore it needs more storage space and it takes long computation time. The FFT is a powerful tool for computing the phase shift between two images. This capability is described in detail in section 2.2 Therefore, the FFT is used in this paper for solving two problems: preliminary data compression and correspondence analysis.

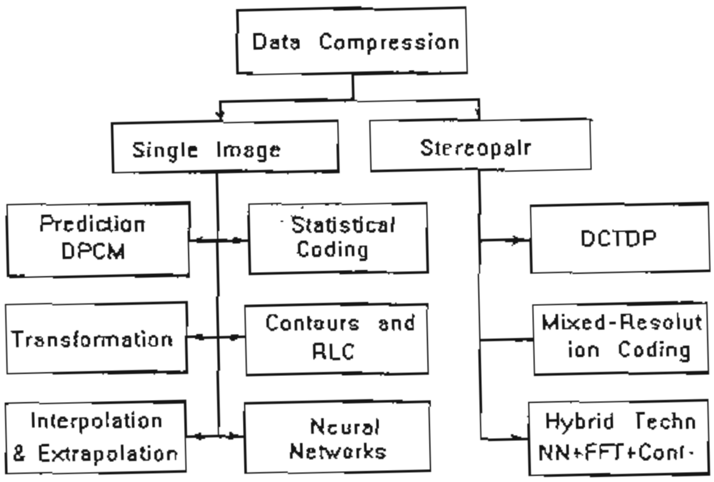


Fig 1. Image Data Compression Techniques

Disparity-compensated transform-domain predictive (DCTDP) coding and mixed-resolution coding [5] seek to minimize the mean square error between the original stereopair and the compressed stereopair. Mixed resolution coding is a perceptually justified technique that is suitable when the compressed stereopair will be viewed by a human. Mixed resolution coding does not attempt to minimize the mean square error between the original stereopair and the compressed stereopair. DCTDP coding typically provides left picture gain on the order 1.0 to 1.5 dB over independent coding of the left picture using the same number of bits. DCTDP coding is more complicated to implement than mixed resolution coding, but it is well suited to a parallel implementation. Mixed resolution coding is easy to implement , and it can reduce the bit rate by 46% with respect to a system that employs no coding. Mixed resolution coding allows a steropair to be transmitted in the bandwidth required for a single uncompressed video channel and it can be applied to either analog or digital systems.

There are several neural network methods which have been developed to deal with data compression. The approaches which have been most explored include the Learning Vector Quantization (LVQ) network for data compression, and special architecture of the network for diemensionality reduction. Recostruction of images which were part of the training set was about 25 dB, and for images which were not of the training set, was about 15 dB [6,15]. Manikopoulis et al. [6] have demonstrated an LVQ-based coding method for image sequences which yield up to 32 dB. The process operates on a spatial domain of 16-dimensional vectors, representing segments of blocks above and to the left of the 16-element block coded. The method combines an intraframe algorithm followed by an interframe algorithm, operating on a bundle of image frames. Both algorithms are based on a finite approach. Storage requirements for the finite states are reduced using the LVQ method.
The hybrid coding has been found to be most appropriate for high quality transmission since it tends to be less sensetive to data statistics and less vulénerable to channel noise, as well be demonstrated in this research. The main advantages of the neural network based hybrid technique to be covered in this work are: amenability to parallel implementation , fault tolerance , learning capability, generalization and noise immunity,

2. A PROPOSED HYBRID TECHNIQUE FOR DATA COMPRESSION:

The proposed technique consists of three processing stages: a neural network based image compressor / decompressor, a phase difference disparity interpreter, and a stereopair reconstructor. Figure 2 shows the block diagram of the proposed data compressor/decompressor, where:

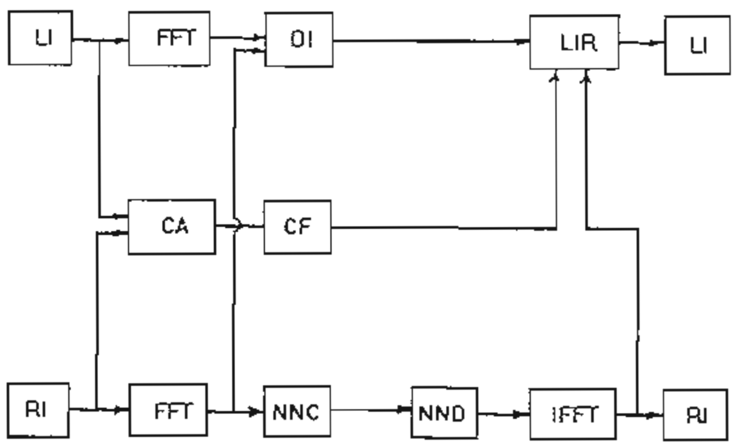


Fig. 2 Schematic of the Data Compression technique

LI :	Left Image	LIR:	Left Image Reconstructor
RI:	Right Image	FFT:	Fast Fourier Transform
CA:	Correspondence Analyzer	NNC:	Neural Network Compressor
CF:	Contour Follower	NND:	Neural Network Decompressor
DI :	Disparity Interpreter	IFFT:	Inverse Fast Fourier Transform

The main advantage of the proposed method lies in a threefold data compression. The first data compression stage is realized by using the Fast Fourier Transform (FFT) for computation of disparity. Data compression is achieved by sending both the disparity values and only the compressed right image. The second data compression stage is achieved by clamping the significant part of the FFT coefficients of the right image to the input layer of the neural network data compressor. This has the advantage of reducing the hardware overhead of the compressor. The third data compression stage is encompassed in the data compression of the previously FFT-compressed right image through the neural net data compressor. At the receiver, the disparity, displaced subimage and the compressed right image are used to reconstruct the left image as will be described in the following sections.

2.1 RANDOM AND REAL STEREOPAIRS:

The simplest stereopairs for testing an algorithm are those that consist of random dot stereograms [7,12]. Random stereograms are a powerful tool for the analysis of both human and machine models for stereopsis. Figure 3 shows the left and right views of random dot stereograms used in the preliminary experiments. The proposed technique has been applied to the real stereopair of the fish shown in Figure 4.

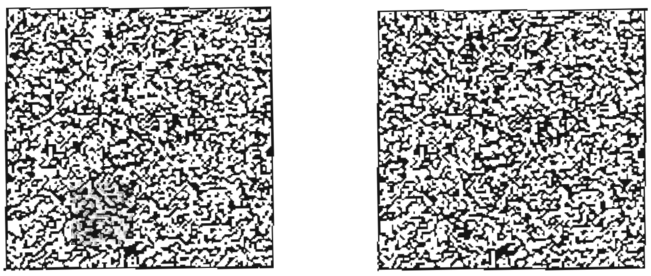


Fig 3. A Random Stereopair

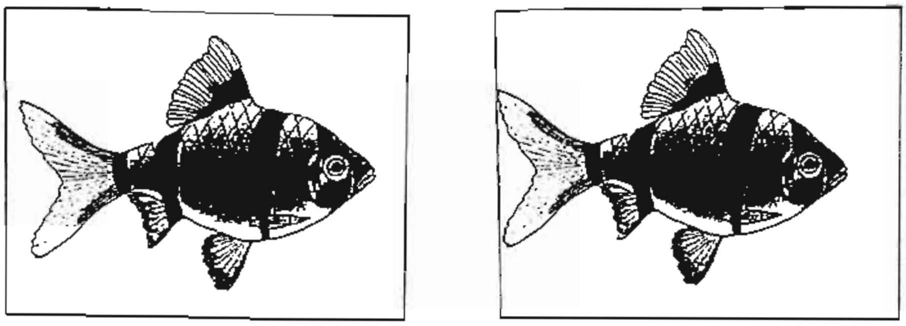


Fig. 4. A Real Stereopair .

2.2 FAST FOURIER TRANSFORM BASED DATA COMPRESSION:

The streopairs under study are of 128x128 pixels resolution. Since such an image size is large to train a neural network. A FFT based data compression ratio of eight is achieved by eliminating the high frequency components of the tested image. This has the advantage of minimizing the overhead in designing the input layer of the neural network compressor / decompressor.

2.3. CORRESPONDENCE ANALYZER (CA):

There are several approaches for solving the correspondence problem of stereopairs : one is to match every point in the left image with that of the right image, another is to extract distinct features (such as lines, or edges) from each image and try to match them [12,14]. The spin system technique is simulated in this work to compute the correspondence of streopairs. The disparity intensity map of an observed scene is first obtained by implementing a spin system model [8,16]. The spin system is characterized by spin variables $S_{ij,}$ which can assume a certain set of values, and by the energy function of the system. In the two-dimensional model the spin variables take the values $\pm$ 1 and the energy of the system is given in [8] by:

$$E = - J \Sigma_{<(i,j),(k,l)>} s_{ij} s_{kl} - \Sigma_{<(i,j),(k,l)>} h_{ij} s_{ij} \qquad (1)$$

In the case of (J > 0) the first term gives negative contribution for equal neighboring spins and, therefore, establishes a tendency for an alignment of the spins. The second term describes the interaction of the spins with a local magnetic field h_{ij} tending to align the spins locally with the field. To use spin systems for pattern recognition, features, e.g. the disparity corresponding pixels, are coded in spins. The pattern to be processed is incorporated in the filed. Global apriori knowledge, like continuity constraints, on the pattern to be interpreted is implemented in the interaction between the feature spins. The energy of the feature spin system is chosen such that the state of the feature spins with the lowest total energy corresponds to the best global interpretation of the pattern. It is achieved by the standard method of Monte Carlo annealing.

In the random dot stereogram shown in Figure 3 , the left image consists of random dots with equal probability for black and white. The right image is similar to the left one except some pixels in a middle region (disparity) of the image which are displaced to the left. Such a stereopair gives the impression of a moving square against a still background when viewd through a steroscope. Since these random dot patterns contain no information, the depth impression results only from the displacement of corresponding pixels. The following four steps are necessary for computing the depth of different image regions :

1. Select a pixel in the left image
2. Find a corresponding pixel in the right image
3. Measure the displacement between both pixels
4. Compute the distance as a function of displacement.

In correspondence analysis, the problem to be soveld is to find the corresponding pixels in both left and right images. This problem is solved by implementing the spin system model. For every pixel of the left image , the direction of the pointer S_{ij} encodes the disparity of the corresponding right image pixel and therefore the distance from the object to the observer. To determine the pointer system directions, which correspond the best stereopair interpretation, the pointer system is assigned an energy, such that a good stereopair interpretation results in lower system energy state. Neighboring spins result in an energy decreasing value for the case of equal disparity, and retain the trend of being parallel directed. A spin system having the minimum total energy results in the best stereopair interpretation. The energy could then be computed according to equation 2 as follows:

$$E = - J \Sigma_{<(i,j),(k,l)>} \delta(s_{ij}.s_{kl}) + \Sigma_{<(i,j),(k,l)>} \left| lpic(i,j) - rpic(i-sij,j) \right| \quad (2)$$

where $\delta(a,b) = 1$ if $a = b$

$= 0$ otherwise

When the energy increases by δE , then the change in energy will be accepted with probability of :

$$p = e^{-\delta E/T} \quad (3)$$

To reach the suitable spin system configuration for the interpretation of the stereopair, the spin system model is simulated by applying random forces on the spins , which result in strong oscillations in the case of higher temperature. By lowering the temperature (random forces) , the spins settle in a position which correponds to the image depth. This cooling process must be slow such that the system does not stuck in a local minimum. The algorithm for this annealing process is as follows:

- Input the parameters: teperature step and number of steps
- Generate a random dot stereopair
- Initialise the spin system to random values
- Repeat for each pixel

    Select a random spin to change its direction
    Compute total energy of spin system
    If (total energy) increases then change this spin direction
    else accept this change with a probability $P = e^{-\delta E/T}$

Until total energy < a prespecified threshold energy

2.4 CONTOUR FOLLOWER (CF):

It is necessary to follow up the disparity map contour to get the outlines of the displaced subimages (image regions) for reconstruction of the left image with a left image reconstructor (LIR) at the receiver.The Freemans chain-code [9] is used for following up the contour of disparity maps by linking up all the border pixels on the contours of the disparity map generated by the spin model. To generate a 8-directional chain code of a given boundary , the following algorithm is implemented:

0- Start
1- Initialize look-up table for a 8-directional chain code
2- Get the direction code for the next point to be traced
3- Repeat

    Get the initial point of each contour to be traced
    Trace the contour
    Mask the already traced image array to avoid backtracking
    Save and plot last contour

  Until last pixel

4- End.

2.5 DISPARITY INTERPRETER (DI):

Disparity relationships between images convey important information for spatial perception. The robustness of the phase difference technique for interepretation of disparity between a pair of stereoscopic images shall be demonstrated. Disparity computation is based on the shift property of Fourier transform given by

$$FFT(f(x-a)) = F(w)\ e^{-2\pi i w a} \qquad (4)$$

where w is the frequency and a is the phase shift. Disparity detecting filters are based on the phase shift property of the Fourier transform, that two functions globaly shifted against each other by the angle delta(x) yield a phase factor of $e^{(j.w.d(x))}$, where w is the frequency. Given a stereopair L(x) and R(x) , left and right images respectively, with a local relative disparity d(x) between them, the FFT transforms of both pictures are locally related to each other as given by

$$R(x,w) = e^{-i\ w\ d(x)}\ L(x,w) \qquad (5)$$

Therefore d(x) = (1/w) arg [R(x,w)/L(x,w)] is a measure of the local disparity. The spin system model implemented in section 2.3 yields a disparity map for real stereopairs. With a combination of several features, e.g. intensities, edges, and lines as input to the disparity interpreter (DI) the algorithm can achieve a better confidence of the disparity interpretation.

2.6 NEURAL NETWORK COMPRESSOR / DECOMPRESSOR :

2.6.1 NETWORK ARCHITECTURE:

The problem of stereopair data compression could be formulated as a supervised learning problem by making the target image equal to the input image (auto-association) and taking the compressed signal from the hidden layer. The input to the hidden connections performs the compression and the hidden-to-output connections do the expansion. The neural network is trained with a multilayer backpropagation network. Figure 6 shows the neural compressor / decompressor network architecture.

The FFT transform coefficients are fed into the neurons of the input layer instead of the samples of the original image in order to reduce the number of input layer neurons and to speed up the training process. The effect of the number of units in the hidden layer and the number of hidden layers is studied to get the optimal network architecture (section 3.2). The output layer has the same number of nodes as the input layer.

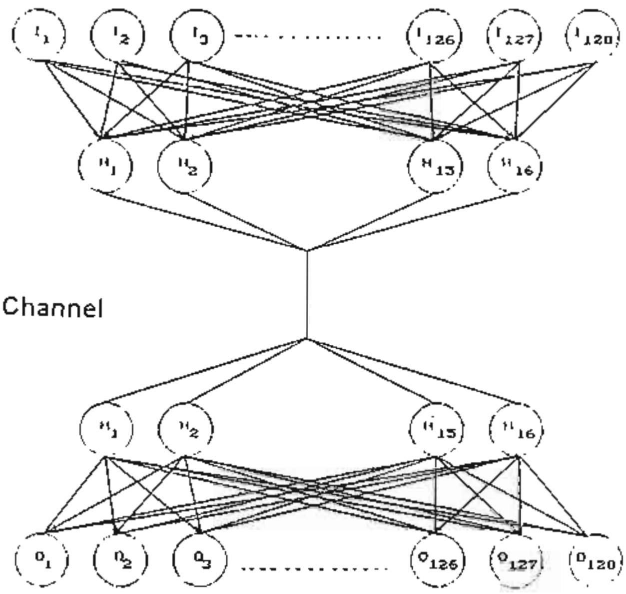


Figure 5 Neural Compressor / Decompressor Architecture

The multilayer perceptron of Figure 6 is a massively parallel structure arranged in several layers of neurons: the input layer, the hidden layer and the output layer. The inputs of every neuron in a given layer are represented respectively by the outputs of the neurons in the preceeding layer for the hidden layer and the inputs of the network for the input layer. Let Y_J be the inputs to a given neuron, then the output X_i is computed as a nonlinear function of the sum of its weighted inputs W_{ji} :

$$X_i = \Sigma_j \quad Y_j \; W_{ji} \qquad (6)$$

The output of neuron i is computed according to the sigmoid function as follows:

$$Y_i = 1 / (1 + e^{(-X_i)}) \qquad (7)$$

The input layer of the network is made up of 128 nodes, each clamped to a FFT coefficient of the input image. The number of output units is the same as that of the input layer. Experiments are conducted on different numbers of hidden layer neurons. The relation between the achieved data compression ratio and the number of hidden layer units is discussed in section 3. It is conducted that the number of hidden layers above one has no significant effect on the data compression ratio.

2.6.2 NETWORK TRAINING:

During the learning phase, the FFT coefficients are presented to the input layer and then processed by the network to compute the outputs of the hidden layer

3. EXPERIMENTAL RESULTS AND DISCUSSIONS:

3.1 SYSTEM ARCHITECTURE:

The proposed hybrid technique has been applied to a number of stereopairs as shown in figure 7. The input video image is digitized with a 512x512 resolution frame-grabber. A binary image is then generated from the acquired gray level image through a dynamic thresholding technique [11]. To keep the size of the neural network needed to solve the problem manageable, we elected to take a small image size of 32 x 32 pixels. The binary image is Fourier transformed to reduce the training time of the neural network. The first 128 significant transform coefficients are used to represent the image. This represents a data compression ratio of 8 (1024/128). The transforms of both left and right images are fed into the disparity analyzer explained in section 2.5 to compute tha disparity. Both left and right images are used to compute the disparity map of the stereopair as discussed in section 2.3. The contour of the localized disparity map is followed with the Freemans chain code as discussed in section 2.4. This contour is a reduced form of the disparity map which adds to the data compression capability of the proposed technique.

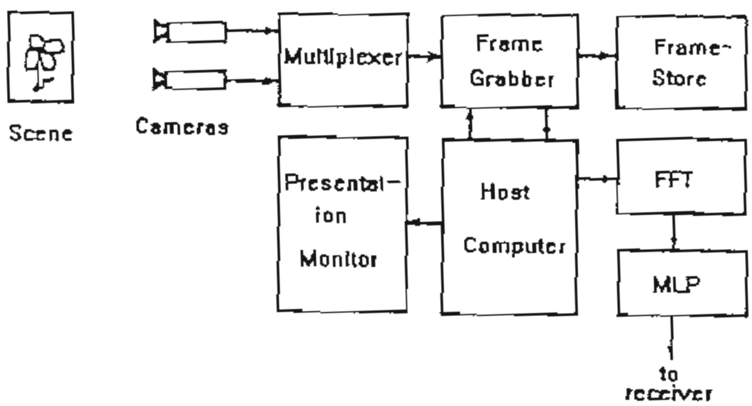


Fig. 6 Schematic representation of the experimental setup.

3.2 COMPRESSION RESULTS OF FFT AND THE NEURAL NETWORK:

The neural network with 128 input neurons and 128 output neurons is trained for image data compression. Different numbers of neurons in the hidden layer are used in order to study their effect on the data compression ratio. Networks with 8,16 and 32 hidden layer neurons are trained on stereopairs. It is found that 8 hidden neurons are sufficient to reconstruct the original image. The experiments show that increasing the number of hidden neurons reduces the training time on the cost of data compression ratio. It is found in our experiments that Increasing the learning rate has no effect on the stability of the network. Table 1. shows the relation between the number of hidden neurons, the number of training epochs and the conducted compression ratio.

Table 1 : Relation between number of hidden neurons and compression ratio.

Hidden Neurons	Training Epochs	Compression Ratio
8	78000	16
16	11000	8
32	8000	4

From table 1 and previous discussions it is concluded that 8 hidden layer neurons are proved to be sufficient for achieving a data compression ratio of 16.

3.3 COMPRESSION RESULTS OF THE CORRESPONDENCE ANALYZER AND CONTOUR FOLLOWER:

Experiments are performed on both random dot stereopairs and real stereopairs to demonstrate the performance of the spin model as a correspondence analysis technqiue. The three design parameters (temperature step T, number of temperature steps TS, vertical and horizontal disparities) that affect the performance of the spin system are studied to conduct the best stereopair interpretation. A Quality Factor (QF) as given by the ratio of the number of desired pixels within the disparity map to the total number of pixels inside it, indicates the convergence of the disparity map construction process. Figure 8. shows the random dot stereopairs and their corresponding results. Decreasing the temperature T results in a stable pattern of the disparities that corresponds to the optimal interpretation of the stereopair (see Figures 8 a,b). Increasing TS results in a better disparity map (see figures 8 a,c). Figures 9 a,b show similar results for random stereopairs with two quadratic disparity regions. Figures 10 a,b,c show a real stereopair for a fish and the corresponding results which agree with those of a random stereopair.

Fig.7a:
T = 0.4
TS = 1
QF = 0.961

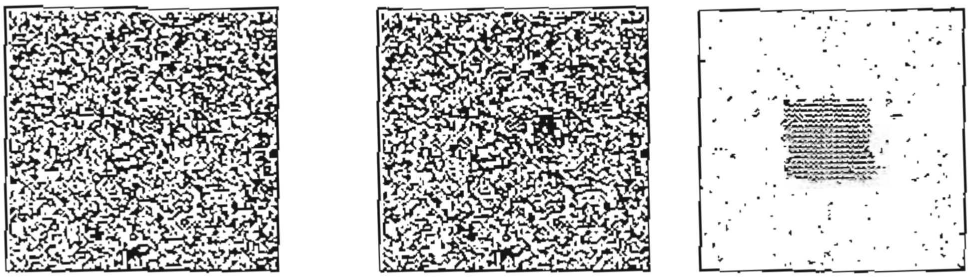


Fig.7b:
T = 0.04
TS = 1
QF = 0.985

Fig.7c:
T = 0.4
TS = 10
QF = 0.964

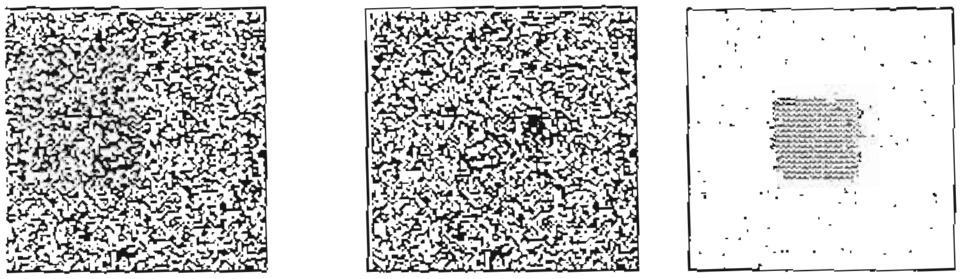


Fig. 8a::
T = 0.04
TS = 1

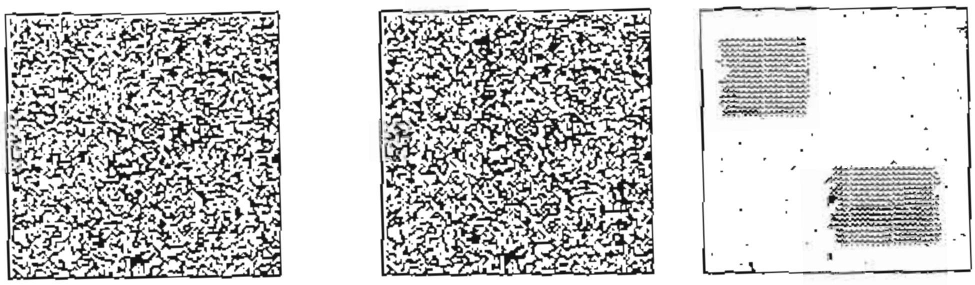
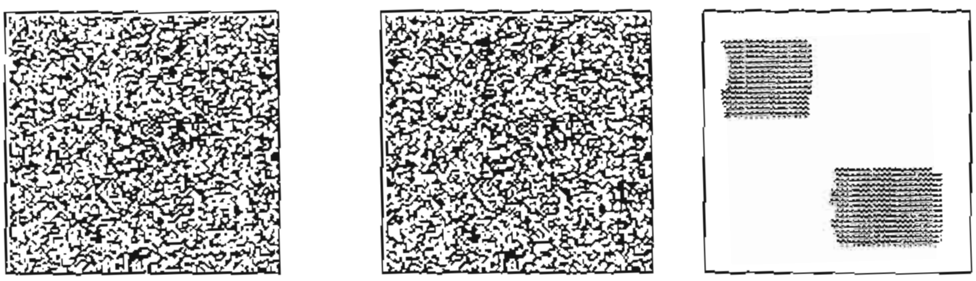


Fig. 8b::
T = 0.04
TS = 10



neurons. The differences between the outputs obtained and the desired targets e (error) are backpropagated in the network to adjust the weights of the connections among the neurons of two adjacent layers:

$$e = 0.5 \Sigma_c \Sigma_i (Y_{i,c} - D_{i,c})^2 \qquad (8)$$

Where $Y_{i,c}$ is the actual output of the ith output neuron and c is the number of the input pattern presented to the input layer, D is the corresponding desired output. The weights in the output layer are updated according to the following equation:

$$W^o_{kj}(t+1) = W^o_{kj}(t) + a\, b^o_{pk}\, i_{pj} \qquad (9)$$

Where $W^o_{kj}(t+1)$ is the weight of the connection between the two nodes k and j for an output layer neuron k at the time t+1, a is the learning rate and b^o_{pk} is the change in the weight of the connection to the output neuron k, i_{pj} is the input to neuron k. The weights of hidden layer are updated according to the following equation:

$$W^h_{ji}(t+1) = W^h_{ji}(t) + a\, b^h_{pj}\, X_i \qquad (10)$$

The weight updating procedure is repeated several times during the learning phase until a prespecified threshold error is reached.

Training a neural network for data compression implies that the matrix of weighting coefficients from the input layer to the hidden layer W^h_{ji} is the inverse of the matrix of weighting coefficients from the hidden to the output layer W^o_{kj} as could be deduced from the following equations:

$$X = W^h\, Y \qquad (11)$$

$$Z = W^o\, X = W^o\, W^h\, Y \qquad (12)$$

Since Y=Z (input=desired output), then $W^o = W^{h^{-1}}$, where Z is the output vector.

2.7 LEFT IMAGE RECONSTRUCTOR (LIR):

The left image reconstructor has three inputs coming from the disparity interpreter (DI), the contour follower (CF), the IFFT of the right image respectively. The disparity, contour of disparity map and right image are necessary to construct the required left image. Results will be given in detail in section 3.3.

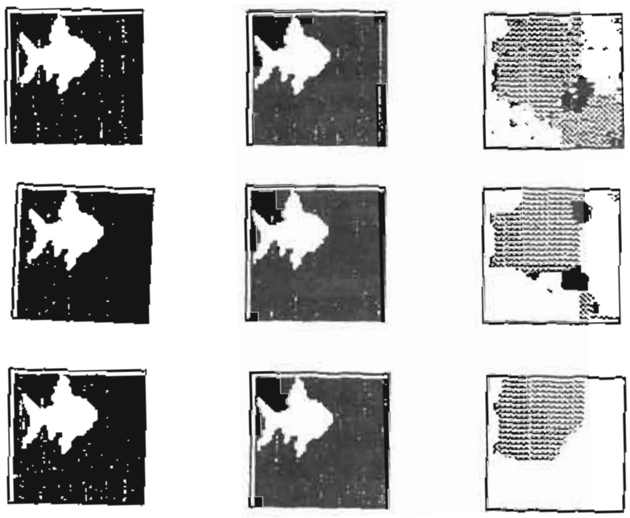


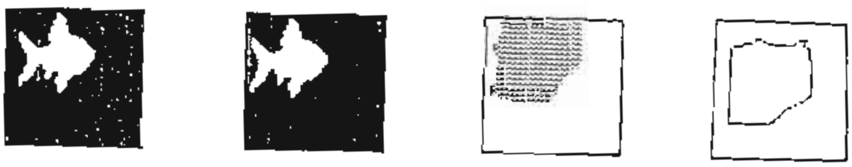
Fig. 10a::
T = 0.4
TS = 20

Fig. 10b:
T = 0.04
TS = 5

Fig. 10c:
T = 0.04
TS = 20

Fig. 9 A real stereopair of a fish and its disparity map at different values of T and TS

From the previous experiments, it is concluded that an accurate estimation of the disparity map is possible through the spin model technique. The disparity map contour shown in Figure 11 is then used with both the disparity and the right image to construct the left image at the receiver as shown in Figure 12. The data compression ratio achieved by the contour follower is found to be (1024 / 230) = 4.45 times, where 1024 is the size of the right image and 230 is the number of pixels on the contour of the disparity map.



T = 0.004
TS = 20

Fig. 10 A fish stereopair, disparity map and its contour .

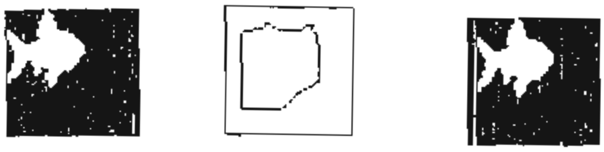


Fig. 11 Right image and contour of disparity map for left image reconstruction.

4. CONCLUSIONS:

A hybrid technique is presented for efficient data compression of stereopairs. The technique includes three data compression stages: FFT coding stage, correspondence analysis and disparity map contour following stage, and neural network based compression stage, respectively. Experimental work is performed on both random and real sterepairs to demonstrate the efficiency of the proposed technique. The low frequency FFT coefficients are fed into the neural network to achieve a preliminary data compression with a ratio of 8 and to speed up the learning phase of the following neural network compressor. A neural network based image compressor / decompressor is designed for compression of both real and random stereopairs. The data compression ratio achieved by the neural network is 16 times. Instead of transmitting a stereopair, the disparity is computed to reconstruct the left image using the disparity, contour of the disparity map and the right image. The problem of disparity analysis is solved using the spin model technique. Experiments are performed to obtain the suitable design parameters for optimal stereopair interpretation.

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