PERFORMANCE OF GRAY SCALED IMAGES USING SEGMENTED CELLULAR NEURAL NETWORK-CELLULAR NEURAL NETWORK COMBINED TRELLIS CODED QUANTIZATION / MODULATION (SCNN-CNN CTCQ/TCM) APPROACH OVER RICIAN FADING CHANNEL

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Abstract: In this paper, Segmented Cellular Neural Network-Cellular Neural Network Combined Trellis Coded Quantization/Modulation (SCNN-CNN CTCQ/TCM) scheme is introduced. Here, a gray scaled image is lowered to 3 bit using our proposed Segmented Cellular Neural Network approach (SCNN) and then passed through a new CNN based structure which models combined trellis coded quantization / modulation. The performance of our combined scheme has been analyzed over Rician fading channel. Computer simulations studies confirm the analytical upper bound curves.

Keywords: *Segmented cellular neural network, trellis code quantization/ modulation, Rician fading channel*

Özet : Bu çalışmada Bölütlenmiş Hücresel Yapay Sinir Ağları-Hücresel Yapay Sinir Ağları Birleşik Kafes Kodlamalı Kuantalama ve Modülasyon işleminin gerçekleştirildiği yeni bir yapı tanıtılmıştır. Burada gri tonlamalı bir görüntü bizim tarafımızdan önerilen Bölütlemeli Hücresel Yapay Sinir Ağı yaklaşımı kullanılarak 3 bit seviyesine düşürülmüş ve daha sonra CNN tabanlı bir modelden oluşmuş kafes kodlamalı kuantalama ve modülasyon yapısından geçirilmiştir. Son olarak bu önerilen yapının performans analiz işlemleri yapılarak simulasyon ve analitik hata başarım eğrileri elde edilmiştir.

Anahtar kelimeler: *Birleşik kaynak / kanal kodlaması, hücresel sinir ağ yapıları*

I. INTRODUCTION

Cellular Neural Network (CNN) (Chua, 1988:1257-1272) with a complex dynamic behaviour have found interesting applications in image processing, pattern recognition. CNN is an analog parallel computing paradigm defined in space, and characterized by locally of connections between processing elements.

To minimize the communication or storage rate and hence the bandwidth or storage capacity required for a given communication and signal processing system, quantization plays a valuable role. If quantization is done before some form of digital signal processing, the subsequent signal processing in principal becomes simpler because of the reduced number of bits required to represent the input signals. In addition, portions of such signal processing can be incorporated into the quantization system so as to ease the computational burden. Here the key becomes the preservation of the information necessary to the application.

In our study, a new CNN approach is introduced for a quantization problem and denoted as 'Segmented Cellular Neural Network (SCNN)'. SCNN helps us to quantize any high levels input images to any order output level. Here since classical CNN output has only two output levels, input high level gray scaled images have been grouped in sub-gray levels. Then each sub-group has passed through a CNN having two different output levels. Thus using SCNN structure, we are able to quantize any high level input data to any desired lower level. As an example SCNN has been applied to Lenna image with 256 gray levels and it has been decreased to 8 gray levels.

During the last two decades, trellis coded modulation (Ungerboeck, 1982:55-67) has proven to be a very effective modulation scheme for band limited channels. Motivated by trellis coded modulation, trellis coded quantization (TCQ) (Marcellin and Fischer, 1990:82-93) was developed as a computationally efficient scheme for source coding. In (Uysal and Uçan, 1997:906-911), TCQ and TCM trellis structures are combined in such a way that the TCQ/TCM system operates on only one identical trellis and is denoted as Combined TCQ/TCM. Here the CNN model has been introduced for the considered trellis structure of Combined TCQ/TCM.

In this paper, the high level gray scaled input image is segmented using the SCNN model and passed through a CNN model of Combined TCQ/TCM structure. The performance of SCNN-CNN CTCQ/TCM scheme has been analysed over Rician fading channel. Computer simulations studies confirm the analytical upper bound curves.

This paper is organised as follows: In Section II, the Cellular Neural Network (CNN) model

is given. In section III, the follows Combined TCQ/TCM is explained. In section IV, the Segmented Cellular Neural Network-Cellular Neural Network Combined Trellis Coded Quantization / Modulation (SCNN-CNN TCQ/TCM) is introduced. In the last section, error performance of SCNN-CNN CTCQ/TCM over Rician Fading channel is investigated and as an example Lenna input image is considered.

II. CELLULAR NEURAL NETWORK (CNN)

CNN is an analog parallel-computing paradigm defined in space, and characterized by locally of connections between processing elements. At the CNN information is only exchanged between neighboring neurons. This local information characteristic doesn't prevent the capability of obtaining global processing. In digital signal processing, discrete time cellular neural network (DT-CNN) (Cimagalli, May: 1993) is applied to some practical problems and can be written by the following equations

$$x(n+1) = Ay(n) + Bu(n) + I$$

$$x_j(n+1) = \sum_{k\in N_{r(j)}} A_{jk}y_k(n) + \sum_{k\in N_{r(j)}} B_{jk}u_k(n)+I_j \qquad (1)$$

$$\mathbf{y}(n) = \frac{1}{2}\left(\left|\mathbf{x}(n)+1\right| - \left|\mathbf{x}(n)-1\right|\right)$$

Where, **A, B, u, y, x, I** denote feedback connection weights matrix, input connection weights matrix, input, output, state and bias respectively. j and k are cell indices and N is the neighborhood function.

III. COMBINED TRELLIS CODED QUANTIZATION/MODULATION (CTCQ/TCM)

In a classical joint TCQ/TCM (Marcellin and Fischer, 1991:172-176; Aksu and Salehi, 1996: 529-533) system, the source is first encoded by a trellis coded quantizer, then modulated by a TCM scheme. The reproduction codebook size (i.e. number of quantization levels) is selected as $N=2^{R+CEF}$. There are totally $N_1=2^{r+CEF}$ subsets. N is chosen so that it can be properly divided by N_1, so each subset has exactly $N_2=N/N1=2^{R-r}$ codewords. Here $R\neq 1$ is the encoding rate in bits/sample, r and CEF are positive integers satisfying $1\leq r\leq R$ and $CEF\neq 0$. The parameter CEF stands for "codebook expansion factor", since the codebook size is 2^{CEF} times that of a nominal R bits/sample scalar quantizer.

The setup of the joint TCQ/TCM system in previous studies is unnecessarily complex. For instance, in the case of the codebook expansion factor is chosen as CEF=1, the TCQ encoder simply generates a sequence of quantization levels from a codebook of size $N=2^{R+1}$ and these levels are mapped to modulation symbols in the 2^{R+1}-point TCM signal constellation. Since there is one-to-one correspondence between the quantization level within a TCQ subset and the modulation symbol within a TCM subset, the cascade organization of TCQ and TCM blocks may be renounced. In (Uysal and Uçan, 1997: 906-911), TCQ and TCM trellis structures are combined in such a way that TCQ/TCM system operates on only one identical trellis.

On the branches of the combined trellis diagram, both quantization levels qk,l which denotes the l^{th} level in the k^{th} quantization subset Qk with k=0,1…N1-1, l=1,2…N_2 and signal set s_j with j=0,1…N-1 are placed using Ungerboeck rules (Ungerboeck,1982:55-67). Thus a single trellis is sufficient to describe the overall combined scheme under the assumption that identical trellises are used. "Combined Trellis Coded Quantization / Modulation" has advantage over classical joint systems in terms of decoding time and complexity (Uysal and Uçan, 1997:906-911).

IV. SEGMENTED CELLULAR NEURAL NETWORK-CELLULAR NEURALNETWORK COMBINED TRELLIS CODED QUANTIZATION/ MODULATION (SCNN-CNN TCQ/TCM)

In this section, 'Segmented Cellular Neural Network (SCNN)' is introduced for quantization application. SCNN scheme quantizes any high level input image to any order output levels. Here since classical CNN output has only two output levels, input high level gray scaled image has been grouped in sub-gray levels. Then each sub-group has passed through a CNN having two different output levels. Thus using SCNN structure, we are able to quantize any high level input data to any desired lower level.

As an example SCNN has been applied to Lenna image with 256 gray levels. At first stage Lenna image is grouped in 4 different gray-scaled levels, each including 64 gray levels. Thus a high level image can be decreased to 8 gray levels by considering each subgroup as a CNN structure having different output levels. Decreased level image at the output of SCNN is transformed to binary sequences in order to apply this information as an input for the CNN model of the combined TCQ/TCM structure given at Figure 2. Since the CNN input and output data size should match each other, we increase the 2 bit input data sequence to 3-bit by stuffing memory information of the trellis scheme (Figure 2). At the CNN equivalent of C TCQ/TCM scheme, modulated output 8PSK signals are modeled by their related binary correspondences, in order to estimate **A, B, I** denoting feedback connection weights matrix, input connection weights matrix and bias respectively,

V. ERROR PERFORMANCE OF SCNN-CNN CTCQ/TCM OVER RICIAN FADING CHANNEL

The basic system under consideration (Fig.1) accepts as input real, continuous amplitude, discrete-time source sequence produced by a memoryless Gaussian source. Combined TCQ/TCM encoder converts the source sequence of length L, $\underline{x}=(x_1, x_2,...,x_L)$ into a sequence of encoder output symbols, which are then block interleaved to break up burst errors caused by amplitude fades of duration greater than one symbol time. At ith signalling interval, the interleaved symbol is mapped into the M-PSK signal where M is given as $M=2^{R+1}$. Corresponding to the M-PSK symbol sequence $\underline{y}=(y_1, y_2,...,y_L)$, a noisy discrete-time sequence $\underline{r}=(r_1, r_2,...,r_L)$ appears at the output of the channel. The received signal at ith signalling interval is expressed as

$$r_i = \rho_i \cdot y_i + n_i \tag{2}$$

where ni is the additive Gaussian noise and is Rician distributed.

At the receiver, first the noise-corrupted sequence is demodulated and deinterleaved, later passed through the combined TCQ/TCM decoder which employs theViterbi algorithm to determine the most likely coded symbol sequence transmitted and produces the output sequence of quantization levels $\underline{\hat{x}}=(\hat{x}_1, \hat{x}_2,...,\hat{x}_L)$ under the assumption that there is one-to-one mapping between quantization levels and modulation symbols. The analytical upper bound can be derived as (Divsalar and Simon 1988:1004-1012).

$$P_b \le \frac{1}{n}\frac{dT(D,I)}{dI}\bigg|_{I=1} \tag{3}$$

$$D^{\beta\rho^2} = \frac{1+K}{1+K+\beta\gamma}\exp\left(\frac{-K\beta\gamma}{1+K+\beta\gamma}\right), \qquad \gamma = \exp\left(-\frac{E_b}{4N_0}\right)$$

Error performance of SCNN-CNN CTCQ/TCM is investigated and upper bounded for Rician Fading channel (Figure 3). At the output of the slowly varying Rician channel, total noise variance σ_t^2 can be written as,

$$\sigma_t^2 = \rho^2\sigma_q^2 + \sigma_n^2 \tag{4}$$

Here, σ_q^2 is the variance of SCNN output and the estimated signal at the receiver. σ_n^2 is the Gaussian noise variance. Thus quantization noise is also included both analytical and simulation results. As an example, Lenna image was applied to the proposed scheme as shown in Figure 1 and the results are also given in Figure 4.

VI. CONCLUSION

In this paper, **Segmented** Celular Neural Network-Cellular Neural Network Combined Trellis Coded Quantization / Modulation (SCNN-CNN CTCQ/TCM) scheme is denoted. Segmented Cellular Neural Network approach (SCNN) is introduced. A new CNN based structure which models combined trellis coded quantization / modulation is investigated. The performance of our combined scheme has been analysed over Rician fading channel. Computer simulations studies confirm the analytical upper bound curves.

References

AKSU H.A. and SALEHI, M. (May 1996) "Joint Optimization of TCQ / TCM Systems", IEEE Trans. Commun., vol. 44, pp. 529-533.

CHUA, L.O. (October 1988), "Cellular Neural Networks: Theory", IEEE Trans. On Circuits and Systems, vol.35, pp.1257-1272.

CIMAGALLI, V. (May 12-14, 1993), "Cellular Neural Networks: A Review", Proceeedings of Sixth Italian Workshop on Parallel Architectures and Neural Networks, Vietri Sul Mare, Italy.

DIVSALAR, D. and SIMON M.K. (September 1988), "The Design of Trellis Coded MPSK for Fading Channels: Performance Criteria" IEEE Trans. Commun., vol. Com-36, pp. 1004-1012.

MARCELLIN, M.W. and FISCHER, T.R. (Jan.1990), "Trellis Coded Quantization of Memoryless and Gauss-Markov Sources", IEEE Trans. Commun., vol. 38, pp. 82-93.

MARCELLIN, M.W. and FISCHER, T.R. (Feb.1991), "Joint Trellis Coded Quantization / Modulation," IEEE Trans. Commun., vol. 39, pp. 172-176.

UNGERBOECK, G. (Jan.1982) "Channel Coding With Multilevel/Phase Signals", IEEE Trans. Inform. Theory, vol. 28, pp. 55-67.

UYSAL, M. and UÇAN, O.N. (1997), "Combined Trellis Quantization/Modulation over Fading Mobile Channel " ACTS Mobile Commun. Summit, pp.906-911, Denmark.

FIGURES

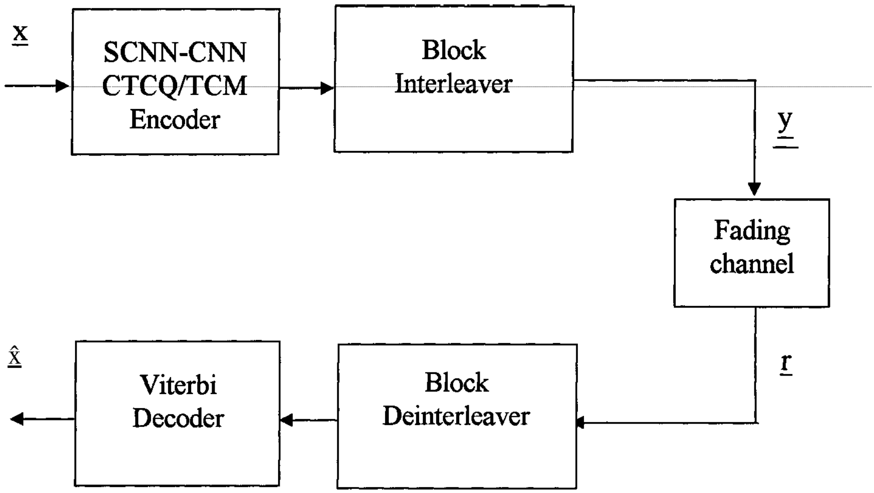

Fig.1. Block diagram of combined SCNN-CNN CTCQ/TCM system.

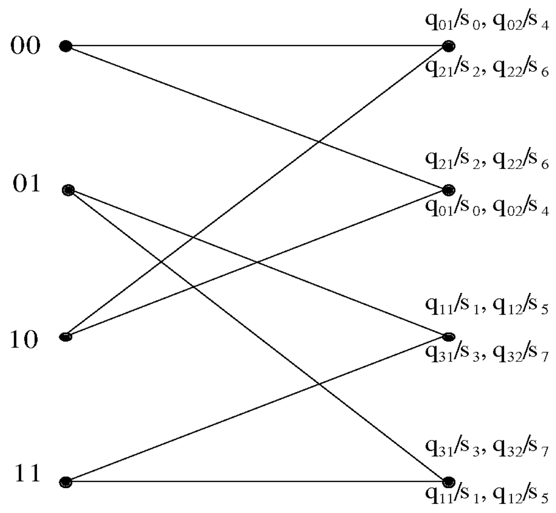

Fig.2. The trellis diagram for 4-state 8-PSK SCNN-CNN CTCQ/TCM system.

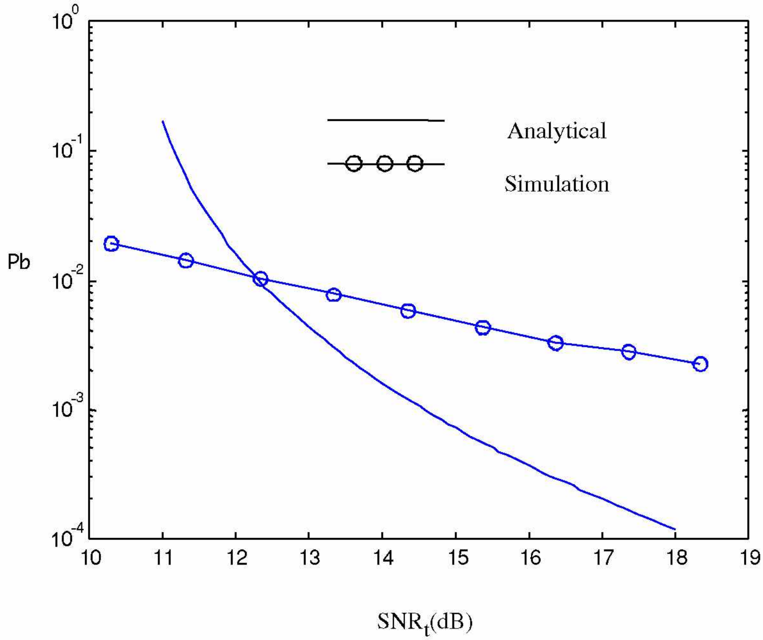

Fig.3. Error performance curves for Rician fading channels (K=5 dB).

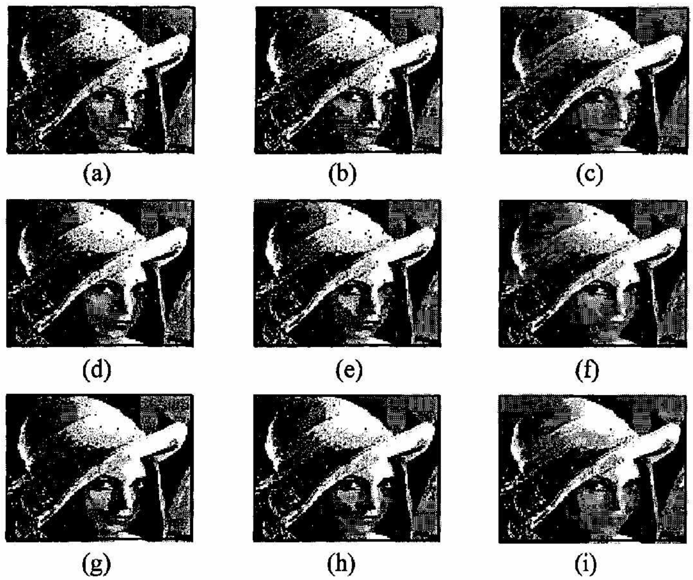

Fig.4. Gray scaled Lenna images at SCNN-CNN CTCQ/TCM decoder output for various SNRt values (a)10.3dB (b) 11.3dB (c) 12.3dB (d) 14.4dB (e) 15.4dB (f) 16.4dB (g) 17.4dB (h) 18.3dB (i) 19.3dB for K=5dB.