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Robust Image Transmission Over Time-varying Channels using Hierarchical Joint Source Channel Coding

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Abstract**—**In this paper, a joint source-channel coding (JSCC) scheme for time-varying channels is presented. The proposed scheme uses hierarchical framework for both source encoder and transmission via QAM modulation. Hierarchical joint source channel codes with hierarchical QAM constellations are designed to track the channel variations which yields to a higher throughput by adapting certain parameters of the receiver to the channel variation. We consider the problem of still image transmission over time-varying channels with channel state information (CSI) available at 1) receiver only and 2) both transmitter and receiver being informed about the state of the channel. We describe an algorithm that optimizes hierarchical source codebooks by minimizing the distortion due to source quantizer and channel impairments. Simulation results, based on image representation, show that, the proposed hierarchical system outperforms the conventional schemes based on a single-modulator and channel optimized source coding.

Keywords**—**Channel-optimized VQ (COVQ), joint optimization, QAM, hierarchical systems.

I. Introduction

In MODERN practical communication systems, like image and video transmission, an efficient scheme can be obtained by jointly optimizing the channel/source encoders. Therefore, many techniques have been proposed with the objective to reduce the bit-rate while maintaining a good quality of the received data [1]-[4]-[5]-[6]. In this context, Farvardin in 1991 [1] has proposed the channel optimized vector quantization (COVQ) that involve in the source encoder some functions of the channel encoder by optimizing the Vector Quantization (VQ) to be robust against the channel noise. Then, the optimized QAM (OQAM) is considered to reduce the distortion due to the channel noise by optimizing the QAM constellation signals [2]-[7]. The OQAM algorithm modifies the positions of the QAM constellation signals into a weighted square constellation, to reach a local minimum of distance between the transmitted QAM signal and the received one. Han in 2001 [3] has proposed an iterative scheme that jointly optimizes the COVQ encoder and the OQAM to minimize end-to-end distortion. This scheme provides good performances, but necessitates a huge amount of computation resources. The channel capacity varies in the time; hence the hierarchical modulation [8] is an efficient solution to this variation. This modulation constitutes one of numerous assets of the DVB-T, allowing another kind of spectrum efficiency usage by addressing various categories of receivers in various situations [10]. In another work [9] an adaptive design scheme is proposed: for L channel state, this scheme optimises the L VQ codebooks by minimizing a distortion including both the quantization noise and the channel distortion so the COVQ algorithm is applied for each VQ codebook. In this paper our proposed scheme combines the hierarchical QAM and a hierarchical-JSCC-modified version of the COVQ algorithm. This designed scheme is referred to as "Hierarchical QAM and Channel Optimized VQ" (H-QAM-COVQ). The performance of the H-QAM-COVQ is evaluated by some simulations which show that this scheme outperforms the COVQ for a fixed QAM–64 in the peak signal-to-noise ratio (PSNR).

II. Proposed Framework

Our framework is most easily explained through an illustrative example of a three-state AWGN channel model. This channel model is insightful as it can be easily generalized to the desired time-varying channel case by considering an L-state AWGN channel, as L gets sufficiently large. So we suppose the channel can be in one of only three different states so $L = 3$. In each state a, the channel is AWGN with a noise variance $(\sigma^a)^2$, with the states being "good" "medium" and "bad". Suppose that the receiver and the transmitter know the actual channel state after guard period. We want to transmit a source quantized through this channel using QAM modulation constellation with a rate $1/T_s$, where T_s is the symbol period. In the receiver the hierarchical QAM constellation and hierarchical VQ codebook are used for decoding, the choice between a different size of constellation and VQ codebook is function of the average Channel Signal to Noise Ratio (CSNR) measured in a period $T = l\ T_s$. In our system model tow threshold th_1 and th_2 for the CSNR are used by the receiver to select the QAM constellation and the VQ codebook that are adapted to the present channel conditions. Nevertheless, L-1 thresholds are used on the presence of L channel states.

The designed system model is represented in figure 1. As shown in this figure, the VQ encoder maps each k-dimensional source vector Y_l into a region Ω_i among the partition $\Phi = \{\Omega_0,\Omega_1,\ldots,\Omega_{N\text{-}1}\}$ of the space IR^k where Ω_i is assumed to be mapped one to one to constellation point S_i. The set $S = \{S_0,S_1,\ldots,S_{N\text{-}1}\}$ forms the QAM signal constellation where N design the number of signals.

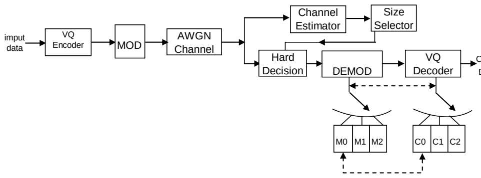

Fig. 1 System model

The modulated signals S_i, i = 0, 1,…, N-1, are assumed to be transmitted over one of the different level of the noisy channel that is exposed to AWGN. The transmitted signal S_i is displaced due to AWGN with a noise variance $(\sigma^a)^2$. A hard decision detector γ^a maps the received signal into a modulation signal S^a_j. The set $S^a = \{S^a_0, S^a_1,\ldots,S^a_{Na-1}\}$ forms the QAM signal constellation used by the decoder where N^a design the number of signals, Note that the set $\{S^a\}_{a=1}^{L=3}$ forms the hierarchical QAM signal constellation used by the decoder (Fig. 2).

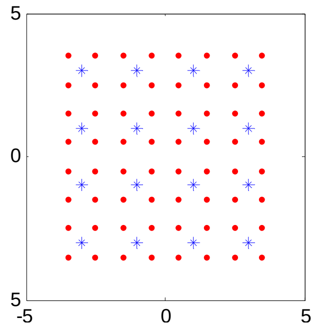

Fig. 2 4 QAM over 16 QAM

The system parameters include the following:

1) The source encoder partitions;
2) The channel modulation constellation;
3) The receiver decision thresholds;
4) The source decoder codebooks containing the reconstruction codewords.

The performance of the above system is measured in terms of the mean squared error (MSE) between the source sample Y_l and its reconstructed vector X^a_j. Let the transition probability $P^a(X^a_j|Y_l\in\Omega_i)$ ($0 \le i < N$; $0 \le j < N^a$-1) denotes the probability of that the codevector X^a_j is received, given that Y_l ($\in\Omega_i$) is transmitted. Then, the overall distortion due to both the quantization and the channel noise is given by

$$D(C,\Phi)=\sum_{a=1}^{L}\sum_{i=0}^{N-1}\sum_{Y_l\in\Omega_i}\sum_{j=0}^{N^a-1}P^a(X^a_j|Y_l\in\Omega_i)\,d(Y_l,X^a_j) \qquad (1)$$

Since both Ω_i and X^a_i are assumed to be mapped into S_i and S^a_i respectively using a heuristic mapping [3], the transition probability is $P^a(X^a_j|Y_l\in\Omega_i) = P^a(S^a_j|S_i)$. Therefore, (1) can be rewritten as

$$D(C,\Phi)=\sum_{a=1}^{L}\sum_{i=0}^{N-1}\sum_{Y_l\in\Omega_i}\sum_{j=0}^{N^a-1}P^a(S^a_j|S_i)\,d(Y_l,X^a_j) \qquad (2)$$

III. Hierarchical QAM-Channel-Optimized VQ

The coding general principal treating the plain hierarchy has been spread through a case of pyramidal decomposition bottom-up type. Our goal is to minimize the distortion $D(C,\Phi)$. For this objective, we apply a Hierarchical-JSCC-modified version of the Channel Optimized Vector Quantization (COVQ) algorithm to optimize the encoder partitions Ω_i which take into consideration the variation of the channel state, after that the algorithm optimizes the decoder reconstruction levels C^a, $a \in \{1,\ldots,L = 3\}$, so that the cost function is minimized. Given that (2) can be rewritten as

$$D(C,\Phi)=\sum_{i=0}^{N-1}\sum_{Y_l\in\Omega_i}\left\{\sum_{a=1}^{L}\sum_{j=0}^{N^a-1}P^a\left(S^a_j|S_i\right)d\left(Y_l,X^a_j\right)\right\} \qquad (3)$$

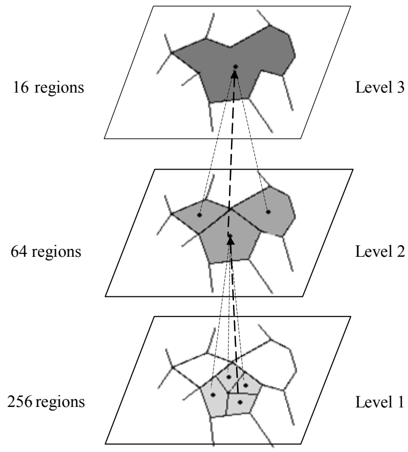

Fig. 3 Construction *Bottom-up* in $IR^{k=2}$

When a particular Y_l belongs to a partition Ω_i^*, the amount of distortion introduced by Y_l becomes

$$D_{Y_l\in\Omega_{i^*}}(C,\Phi)=\sum_{a=1}^{L}\sum_{j=0}^{N^a-1}P^a\left(S^a_j|S_i\right)d\left(Y_l,X^a_j\right) \qquad (4)$$

Thus, for each Y_l, a partition number i^* should be chosen to minimize $D_{Y_l\in\Omega_{i^*}}(C,\Phi)$. The optimum partition $\Phi = \{\Omega_0,\Omega_1,\ldots,\Omega_{N-1}\}$ is found as

$$\Omega_i=\left\{Y_l,\sum_{a=1}^{L}\sum_{j=0}^{N^a-1}P^a\left(S^a_j|S_i\right)\,d\left(Y_l,X^a_j\right)\le \sum_{a=1}^{L}\sum_{j=0}^{N^a-1}P^a\left(S^a_j|S_n\right)\,d\left(Y_l,X^a_j\right),\forall\, n, 0\le l<Q\right\} \qquad (5)$$

where Q represents the number of training source vectors. For a fixed encoder partitioning Φ, we optimize iteratively the L reconstruction hierarchical codebooks C^a and we design the optimums partitions Φ^a; $1 \le a \le L = 3$. In our proposed algorithm we suppose that, $N^1 > N^2 > \ldots > N^L$ and N^1 partitions Ω_i forms the encoder partitioning Φ, so $\Phi^1 \equiv \Phi$; Φ^1

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design the optimum partition of the decoder codebook C^1, after, for a fixed Φ^1, the optimum codebook C^1 is obtained as

$$X_i^1 = \arg\min_{y \in R^k} E\left(d(Y_l, y) \,\middle|\, Y_l \in \Omega_i\right) \qquad i \in \{0,1,\dots,N^1-1\} \tag{6}$$

Then the optimum partition Φ^2 which design the lower hierarchy of level 1 is found as

$$\Omega_i^2 = \bigcup_{j \in Q_i^1} \Omega_j \quad i \in \{0,1,\dots,N^2\text{-}1\} \tag{7}$$

Where

$$Q_i^1 = \left\{n : d\left(X_n^1, X_i^2\right) \le d\left(X_n^1, X_k^2\right), \forall k\right\} \tag{8}$$

Afterwards the optimum codebook C^2 is obtained as

$$X_i^2 = \arg\min_{y \in R^k} E\left(d(Y_l, y) \,\middle|\, Y_l \in \Omega_i^2\right) \qquad i \in \{0,1,\dots,N^2-1\} \tag{9}$$

TABLE I
HIERARCHICAL JSCC ALGORITHM

Step 1	Initialize the encoder partition Φ, and decoder reconstruction codebook C^a, $1 \le a \le L$ using a VQ; a = 1.
Step 2	$iter = 1$, $D(C, \Phi)^{(0)} = \infty$.
Step 3	Optimize Ω_i , $i = 0, 1, \dots, N^L\text{-}1$ by (5).
Step 4	Compute the optimal X_i^a , $i \in \{0,1,\dots,N^a\text{-}1\}$ by (6).
Step 5	a++; Optimize Ω_i^a , $i = 0, 1, \dots, N^a\text{-}1$ by (7); Compute the optimal X_i^a , $i \in \{0,1,\dots,N^a\text{-}1\}$ by (9).
Step 6	If a = L, stop, else go to Step 5.
Step 7	If $\{D(C, \Phi)^{(iter\text{-}1)} - D(C, \Phi)^{(iter)}\} / D(C, \Phi)^{(iter\text{-}1)} > \varepsilon$, then $iter = iter + 1$ and go to Step 3.
Step 8	Stop.

A successive application of (5), (6), (7), (8), and (9) results in the convergence to a local minimum as the LBG and COVQ algorithms do (Fig. 4). Our proposed algorithm is summarized in Table I.

IV. NUMERICAL RESULTS

Computer simulation using fixed images was performed to evaluate the performance of the proposed scheme.

TABLE II
SIMULATION CHARACTERISTICS

Channel State	Bad	Medium	Good
CSNR (dB)	11.54	17.65	23.63
Size	16	64	256

In designing the H-QAM-COVQ codebooks, some different monochromatic images including "baboom", "barbara", "toy", and "bridge" images are used as the training data (Q = 60000 vectors). Each pixel of all images is represented by 8 bits. In the simulations, the codevector dimension is k = 16 and the size of the VQ codebook take value in the set {16,64,256}. We suppose that the channel varies 3 times among the 3 states. The 512 × 512 "goldhill" image which is not in the training image set is used in the simulation to measure the algorithm performance. The results are presented in terms of the PSNR of the received image data as a function of the CSNRs. The CSNR is defined as:

$$\mathrm{CSNR}^a \equiv 10\log_{10}\frac{E^a}{No} \tag{10}$$

and

$$E^a = \frac{1}{N^a}\sum_{i=0}^{N^a-1}\left|S_i^a\right|^2 \tag{11}$$

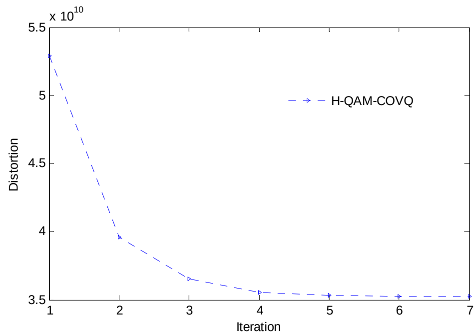

Fig. 4 Convergence of the algorithm as the iteration number increases

Fig. 4 shows variations of values of $D(C,\Phi)$ as the iteration number increases. the proposed system is compared to the initial system COVQ256 + CSNR = 23.63 dB. In the Fig. 5, we have plotted the PSNR measured after the receiving of each 541-symbol bloc.

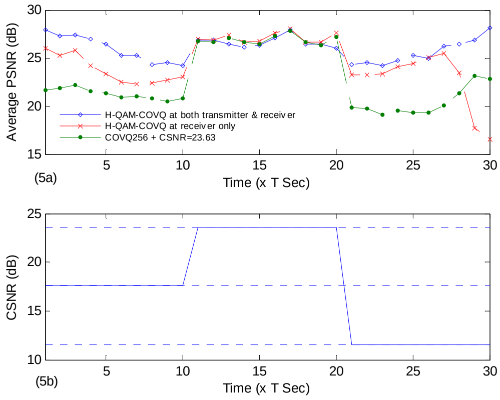

Fig. 5 Performance of the proposed algorithm

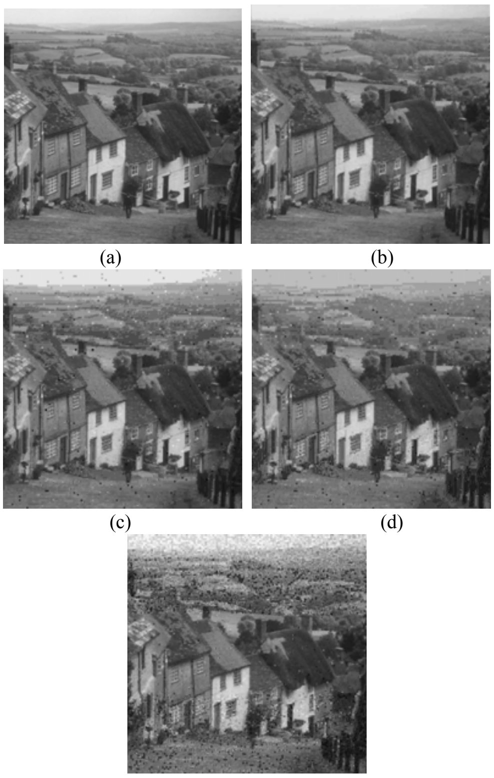

Fig. 6 (a) Original goldhill 8-bit image; (b) goldhill + Quantization error (PSNR = 29.08 dB) (c) The reconstructed image using the proposed scheme at transmitter and receiver (PSNR = 25.91 dB); (d) The reconstructed image using the proposed scheme at receiver only (PSNR = 23.68 dB); (e) The reconstructed image using the initial system QAM-COVQ256 + CSNR = 23.63 dB (PSNR = 21.76 dB);

On one hand, the figure shows that, for high CSNR (CSNR = 23.63 dB), the proposed system has not lost its performance compared to the initial system, despite that the system has been conceived taking into consideration the 3 channel states. On other hand, for low CSNR i.e when the channel state varying between "medium" and "bad", the proposed system outperforms the initial system in term of PSNR. This sums up the H-QAM-COVQ algorithm stake. It can be seen from the figure that a perceptually significant improvement can be obtained by using the proposed scheme in the case of transmitter and receiver being informed about the state of the channel, the performance is enhances about 2 dB in term of PSNR. The Fig. 6 shows the subjective effects of the proposed algorithm, the proposed algorithm outperform the initial algorithm of about 2 dB.

V. Conclusion

We have introduced a natural and efficient hierarchical based framework to do joint source-channel coding and formulated an efficient modified version of the COVQ algorithm to accomplish this. Our basic idea is derived from the simple concept of optimally matching the source hierarchy to the channel "hierarchy." By having a multi-hierarchical "menu" of hierarchies, the decoder has the flexibility of selecting the levels that is optimal for a given channel condition. Knowing that the receiver is informed of the CSI, it can adapt to it. If the channel gets "bad," the source hierarchy is lowered because operating at full hierarchy does more harm than good. When the channel gets "good," the hierarchy can be increased. In our particular system, we show that 2 dB of gain in PSNR are typically realizable by invoking a multi-hierarchical-based JSCC approach over source-channel optimized single resolution designs based on standard modulation constellations.

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