Available online at www.sciencedirect.com
SCIENCE DIRECT®
ELSEVIER
Pattern Recognition Letters 25 (2004) 793–806
Pattern Recognition Letters
www.elsevier.com/locate/patrec

Stochastic channel-adaptive rate control for wireless video transmission

R. Chandramouli [a,*], K.P. Subbalakshmi [a], N. Ranganathan [b]

[a] *Department of Electrical and Computer Engineering, Stevens Institute of Technology, USA*
[b] *Department of Computer Science, University of South Florida, USA*

Abstract

In this paper, an empirically optimized channel-matched quantizer, and a joint stochastic-control based rate controller and channel estimator for H.261 based video transmission over a noisy channel is proposed. The rate controller adaptively learns to choose the correct channel matched quantizer using a stochastic learning algorithm. The stochastic automaton based learning algorithm aids in estimating the channel bit error rate based on a one bit feedback from the decoder. The algorithm is observed to converge to the optimal choice of the quantizer very quickly for various channel bit error probabilities and for different video sequences. When compared to traditional channel estimation schemes the proposed technique has several advantages. First, the proposed method results in a significant reduction in the delay and bandwidth requirement for channel estimation when compared to pilot symbol aided channel estimation schemes. Next, the stochastic learning algorithm used to estimate the channel bit error rate has simple computations. This makes it attractive for low power applications such as wireless video communications. This is in contrast to traditional blind channel estimation schemes that are computationally expensive, in general.

1. Introduction

Multimedia applications such as the wireless video transmission have lead to the study of issues in error-resilient low bit-rate video transmission over noisy channels. Wireless links not only suffer from limited bandwidth problems but are also highly vulnerable to channel errors. Video compression standards like the H.261 (Bhaskaran and Konstantinides, 1995) alleviate the bandwidth problem to a certain extent. The H.261 standard also known as the $p \times 64$ standard was developed for video coding and decoding at the rate of $p \times 64$ kbits/s, where p is an integer from 1 to 30.

Most of the *state-of-the-art* video codecs treat source and channel coding separately. Bandwidth reduction is achieved by the source coder by removing the redundancy in the source statistics. Error protection against channel error is take care of by the channel coder through the addition of redundancy in the transmitted data. However, this separation is justifiable only in the limit of an arbitrary encoding/decoding complexity. But, we know that in practice complexity and delay are the main constraints for communication systems.

* Corresponding author.
E-mail addresses: mouli@stevens-tech.edu (R. Chandramouli), ksubbala@stevens-tech.edu (K.P. Subbalakshmi), ranganat@csee.usf.edu (N. Ranganathan).

0167-8655/$ - see front matter
doi:10.1016/j.patrec.2004.01.003

Therefore, the separation of source and channel coding is no longer optimal. This implies that source and channel coding should depend on each other leading to *joint source–channel coding* (JSCC) (Kurtenbach and Wintz, 1969).

JSCC has been receiving significant attention lately as a viable solution for achieving reliable communication of signals across noisy channels. The rationale behind using such techniques is the observation that Shannon's source–channel separation theorem (Shannon, 1949) does not usually hold under delay and complexity constraints or for all channels (Vembu et al., 1995). JSCC tries to design the source coder and channel coder in some joint way, which can provide better error protection and bandwidth utilization. JSCC schemes can be broadly classified into three different categories, *joint source–channel encoding* (JSCE) (Dunham and Gray, 1981; Farvardin, 1990; Phamdo et al., 1997), *joint source–channel decoding* (JSCD) (Sayood and Borkenhagen, 1991; Sayood et al., 1994; Phamdo and Farvardin, 1994; Park and Miller, 1997, 2000; Demir and Sayood, 1998; Wen and Villasenor, 1999; Bauer and Hagenauer, 2000a,b; Hedayat and Nosratinia, 2002; Kliewer and Thobaben, 2002; Guivarch et al., 2000; Subbalakshmi and Vaisey, 1998, 1999a,b, 2001, in press; Murad and Fuja, 1998a,b; Lakovic et al., 1999; Lakovic and Villasenor, 2002; Alajaji et al., 1996; Burlina and Alajaji, 1998; Kopansky and Bystrom, 1999; Bystrom et al., 2001; Subbalakshmi and Chen, 2002; Chen and Subbalakshmi, 2003) and rate allocation strategies (Hochwald and Zeger, 1997; Bystrom and Modestino, 1998; Cheung and Zakhor, 2000). As the names suggest, these deal with the joint design of encoders, decoders and the rate allocation between the channel and source codes respectively. One early work in this class is by Dunham and Gray (1981), where they demonstrate the existence of a joint source–channel system for special source and channel pair, by showing that a communication system using trellis encoding of a stationary, ergodic source over a discrete memoryless noisy channel can perform arbitrarily close to the source distortion-rate function evaluated at the channel capacity. Other works include an index assignment algorithm proposed for the optimal vector quantizer on a noisy channel (Farvardin, 1990) and the design of quantizers for memoryless and Gauss–Markov sources over binary Markov channels (Phamdo et al., 1997).

Work on rate allocation between the channel and source codes includes the optimal allocation algorithm between a vector quantizer and a channel coder for transmission over a *binary symmetric channel* (BSC) (Hochwald and Zeger, 1997), the optimal source–channel rate allocation to transmit H.263 coded video with trellis-coded modulation over a slow fading Rician channel (Bystrom and Modestino, 1998) and an algorithm to distribute the available source and channel coding bits among the sub-bands of scalable video transmitted over BSC to minimize the expected distortion (Cheung and Zakhor, 2000).

JSCD schemes can be further classified into *constrained* JSCDs and *integrated* JSCDs. Constrained JSCDs are typically source decoders that are built using prior knowledge of channel characteristics while integrated JSCDs combine the source and channel decoder into one unit. One example of constrained JSCD for fixed length encoded sources is the work of Sayood and Borkenhagen (1991), who investigated the use of residual redundancy left in the source after coding it with a *differential pulse code modulation* (DPCM) source coder in providing error protection over a BSC. This was then extended to include conventional source coder/convolutional coder combinations (Sayood et al., 1994). Other work in this class includes the design of a MAP detector for fixed length encoded binary Markov source over a BSC (Phamdo and Farvardin, 1994) and a MAP decoder for hidden Markov source (Park and Miller, 1997). Channel-matched source rate control or quantization has been shown to be an effective way to add error-resilience to the transmission of compressed images and video over noisy channels (Kurtenbach and Wintz, 1969; Shannon, 1949; Vembu et al., 1995; Dunham and Gray, 1981; Farvardin, 1990; Phamdo et al., 1997; Sayood and Borkenhagen, 1991; Sayood et al., 1994; Phamdo and Farvardin, 1994; Park and Miller, 1997, 2000; Demir and Sayood, 1998; Wen and Villasenor, 1999; Bauer and Hagenauer, 2000a,b; Hedayat and Nosratinia, 2002; Kliewer and Thobaben, 2002; Guivarch et al., 2000; Subbalakshmi and Vaisey, 1998, 1999a,b, 2001, in press; Murad and Fuja, 1998a,b; Lakovic et al., 1999; Lakovic and Villasenor, 2002; Alajaji and Fuja, 1994; Alajaji et al., 1996; Burlina and Alajaji, 1998; Kopansky and Bystrom, 1999; Bystrom et al., 2001; Fano, 1963; Subbalakshmi and Chen, 2002; Chen and Subbalakshmi, 2003; Hochwald and Zeger, 1997; Bystrom and Modestino, 1998; Cheung and Zakhor, 2000; Chandramouli et al., 1998a).

The H.261 standard recommends the use of Huffman encoding to achieve an additional gain in the compression ratio. But, it is known that variable length codes are highly susceptible to channel errors. The critical bits need to be protected from channel errors in order to prevent the complete loss of a transmitted video sequence. If, during transmission some bits are flipped, added or dropped, the synchronization of the decoder to the received bit stream could be lost. This leads to error propagation and the loss of the source symbols. The loss of a few blocks of symbols causes displacements in the received image. Error correcting codes can be used to protect the critical bits from channel errors. Examples of the critical bits are the EOB (end of block) markers and the most significant bit of a source symbol. An error in the most significant bit could cause higher degradation than a corrupted least significant bit. The loss of EOB due to errors leads to catastrophic error propagation as shown in Fig. 1. Therefore, the high priority bits need to be protected using channel coding or other methods. But the redundancy due to channel coding reduces the effect of the compression efficiency. Therefore, an optimal trade-off between the rate of the source coder and the channel coder is essential.

Channel-matched source quantization and adaptive source rate control based on the channel characteristics are effective ways of reducing the effects of channel noise on the received video signal. However, the performance depends on how fast and reliably the channel parameters (such as the bit error probability p_e) can be estimated. In many applications, p_e is computed using pilot symbol aided techniques. This causes large delays which may not be acceptable for real-time applications. It has also been observed that up to a 14% loss in capacity can be incurred due to pilot symboling (Cavers, 1991). Therefore, it is desirable to reliably estimate the channel statistics and also achieve rate control through adaptive quantization *on the fly* with minimal overhead.

In this paper, a channel-matched quantizer, and a fast and reliable simultaneous rate control and channel estimation algorithm based on the stochastic learning automaton (Narendra and Thathachar, 1989) for a H.261 based video codec over channels that cause random bit errors is proposed.

(a) (b)

Fig. 1. Effect of error propogation. (a) Original image, (b) error propagated image.

A stochastic learning automaton at the encoder estimates and tracks the channel bit error probability. For simplicity, we only consider $p_e = 10^{-1}$, 10^{-2} and 10^{-3} only in this work as they are typical of the wireless channels. However, we note that this method can be extended to finite state channel models with more number of states by expanding the action set of the learning automaton. The learning is based on a one bit decision feedback from the decoder summarizing the peak signal to noise ratio (PSNR) of the received video frames for a particular choice of the source quantizer. The optimal quantizer (and hence the bit rate due to the one-to-one mapping) for that channel bit error probability is learnt and selected by the learning automaton using a linear reward inaction (LRI) learning scheme. We realized that the LRI scheme has absorbing barriers (Narendra and Thathachar, 1989). One way to overcome this would be to trigger the learning process if the received video quality is consistently below a certain threshold. There is no additional overhead of pilot symbols in the proposed approach. We also note that the proposed technique is particularly suited for low power wireless video applications where computationally simplicity in encoding and decoding is emphasized. The system designer has the flexibility to control the convergence rate of the learning algorithm depending on the reliability and delay constraints. To our knowledge, this is the first attempt in using stochastic learning automaton for rate control in low-bit rate video transmission. In order to prevent sync losses at the decoder, the fast error resilient entropy code in (Chandramouli et al., 1998b) is also used. We organize the paper as follows. In Section 2 the channel-matched quantization technique is discussed. The variable structure stochastic learning automaton is introduced in Section 2.3 followed by the rate control and channel estimation algorithm. Performance of the proposed algorithm is studied in Section 3 and concluding remarks are given in Section 4.

2. Quantizer design

The proposed H.261 based video codec is shown in Fig. 2. The adaptive quantizer is

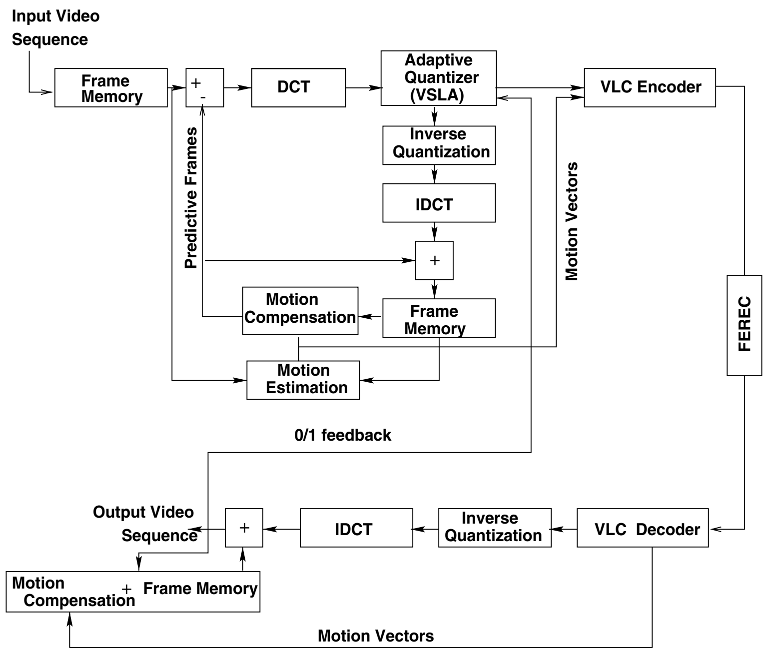

Fig. 2. Proposed H.261 based codec.

implemented using a VSLA. This will be discussed subsequently. To prevent synchronization loss due to error propagation in the variable length coded transmitted data a error-resilience code called FEREC (Chandramouli et al., 1998c) is used. We now discuss a channel matched source quantization scheme. This is similar to the one proposed for the transmission of JPEG compressed images (Chandramouli et al., 1998c). The video frames are categorized into two classes, namely, the intra frame or the I-frame and the predicted frame or the P-frame. One in every 32 frames are intra frame coded. The I-frame coding is similar to the JPEG still image coding which consists of the discrete cosine transform (DCT), quantization and Huffman encoding. The P-frame coding is based on DPCM and motion estimation. I-frames are coded without reference to the preceding frames; whereas the P-frames are coded with respect to the temporally closest preceding I/P-frame. In P-frame coding the best match for each macroblock of the current frame is found in a search area in the previous intra frame using a block matching technique. The two macroblocks are subtracted and the difference is transformed using DCT, quantized and Huffman encoded. Motion estimation is done based on an exhaustive search based block matching technique (Borko and Westwater, 1997). The quantization of the DCT coefficients is implemented based on scaling each coefficient by an entry in the quantization table (Bhaskaran and Konstantinides, 1995). We assume that the same quantization table is used for I and P frames in this paper for simplicity. However, the proposed joint rate control and channel estimation is independent of this assumption. The quantization table for 8×8 DCT blocks used for the simulations is shown in Fig. 3. Clearly, the DC coefficient and the low frequency AC coefficients are finely quantized. The high frequency AC coefficients which have less energy are coarsely quantized.

8	16	19	22	26	27	29	34
16	16	22	24	27	29	34	37
19	22	26	27	29	34	34	38
22	22	26	27	29	34	37	40
22	26	27	29	32	35	40	48
26	27	29	32	35	40	48	58
26	27	29	34	38	46	56	69
27	29	35	38	46	56	69	83

Fig. 3. Quantization table.

2.1. Channel matched source quantization

Errors in the received frame are both due to the quantization and channel errors. At high bit error rates, p_e, a high rate quantizer is more sensitive to the channel errors (Kurtenbach and Wintz, 1969). This causes many received blocks of data to be in error. Therefore, by adjusting the quantization rate to match the channel bit error rate error-resilience can be achieved. The quantization rate can be varied by multiplying each entry in the quantization table by a quantizer factor, say, M. When a coarse quantizer is used by increasing the quantizer factor, M, for a given p_e the errors in the received signal reduce. It reaches a minimum for the optimal choice, namely, M^*. If the bit rate is reduced further then the quantization errors contribute significantly to the degradation in the received signal. The number of blocks in error increases again. Hence, it is necessary to compute the optimal quantization parameter for the *channel limited* or *quantizer limited* region. In other words, if X denotes the source video frame, U is the quantized frame and V is the received frame, then the reconstruction error variance for transmission over a noisy channel is given by

$$\begin{aligned}\sigma^2_{\text{rec}} &= \boldsymbol{E}[X-V]^2 = \boldsymbol{E}[(X-U)+(U-V)]^2 \\ &= \boldsymbol{E}[X-U]^2 + \boldsymbol{E}[U-V]^2 \\ &\quad + 2\boldsymbol{E}[(X-U)(U-V)] \\ &= \sigma^2_{\text{q}} + \sigma^2_{\text{c}} + 2\sigma^2_{\text{m}} \end{aligned} \tag{1}$$

The quantities σ^2_{q}, σ^2_{c} and σ^2_{m} denote the quantization, channel and the mutual error variance. The contribution of σ^2_{m} can be neglected for a small bit error probability. However, we account for this in our simulations. Under noise free conditions the quantization error variance is minimized using the

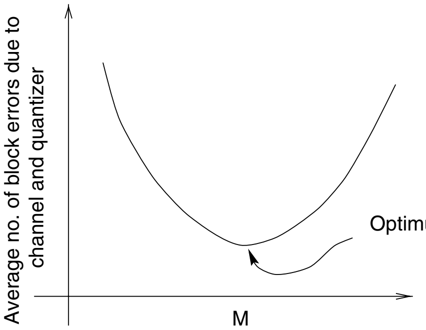

Fig. 4. A typical Q–C curve.

perceptually optimized quantization values given in Fig. 3. When the channel is noisy, σ_c^2 is minimized by a proper choice of the quantizer parameter, M. Therefore, σ_{rec}^2 is minimized by the optimal choice of M. Thus, the optimal value M^* is a function of σ_q^2 and σ_c^2 as shown in Fig. 4. Computing a closed form solution for M^* may not be possible due to the presence of VLC. Therefore, we resort to simulative methods.

2.2. Q–C modeling

A model that relates the number of block errors in the reconstructed frame and M is developed in this section. The parameters of the model are computed using extensive simulations for bit error rates ranging from 10^{-3} to 10^{-1}. The channel is assumed to cause random bit errors. We call the quantizer-channel error trade-off as the *Q–C curve* (Chandramouli et al., 1998a). The rate of the quantizer can be adapted to the channel bit error rate by suitably changing M. The value of M is increased in steps of 0.2 for a fixed p_e and the number of significantly corrupted reconstructed blocks are computed. The higher the value of M the coarser is the quantization. The I-frames are assumed to be sufficiently protected from channel errors and there are 30 P-frames between any two I-frames. The successive received frames are reconstructed from the nearest I-frame after motion compensation. A 8×8 reconstructed image block is termed erroneous if the PSNR of the reconstructed block defined as

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\frac{1}{N^2}\sum_{i=0}^{i=N-1}\sum_{j=0}^{j=N-1}(X(i,j)-V(i,j))^2}\right) \tag{2}$$

is less than 30 dB. The Q–C curve is the average number of erroneous blocks averaged over a number of video frames and sequences for various values of M. This produces a Q–C curve for that p_e. The same procedure is repeated for other channel bit error rates also. The experimental Q–C curves (non-smooth) are shown in Figs. 5–7. A

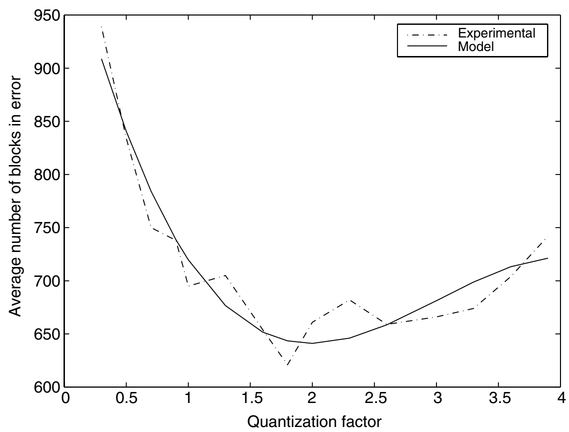

Fig. 5. Q–C curve for $p_e = 10^{-1}$.

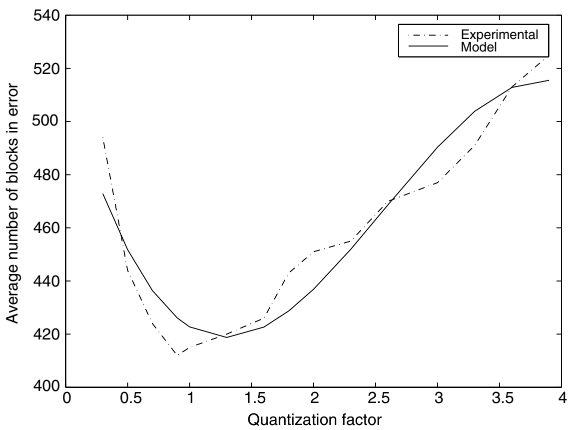

Fig. 6. Q–C curve for $p_e = 10^{-2}$.

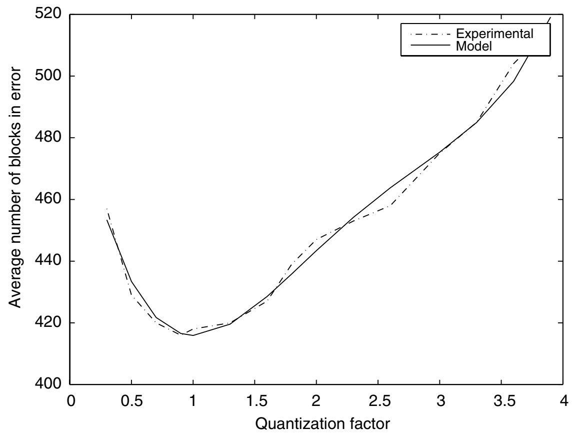

Fig. 7. Q–C curve for $p_e = 10^{-3}$.

second order regression model for the average number of blocks in error is fitted to the experimental results shown as the solid curve. The optimal value of the quantizer factor, M^* minimizes the average number of blocks in error in the regression model. The optimal quantizer values are given in Table 1. For example Fig. 8(a) and (b) shows the received frame for $p_e = 10^{-2}$ for two different quantizers. We see that using the value of M^* from Table 1 for this bit error rate results in a reduction in the total number of corrupted blocks.

Table 1
Look-up table for M^*

p_e	M^*
10^{-1}	2
10^{-2}	1.3
10^{-3}	1

A similar performance improvement is seen for other bit error rates also.

2.3. Stochastic learning automaton

In this section we briefly discuss the concept behind the variable structure stochastic learning automaton (VSLA) (Narendra and Thathachar, 1989). Fig. 9 shows the schematic of the stochastic learning automaton. Abstractly, a learning automaton can be considered to be an object that can choose from a finite number of actions. For every action that it chooses, the random environment in which it operates evaluates that action. A corresponding feedback is sent to the automaton based on which the next action is chosen. As this process progresses the automaton learns to choose the *optimal* action asymptotically. The rule used by the automaton to select its successive actions based on the environment's response defines the stochastic learning algorithm. An important property of the learning automaton is its ability to improve

(a) (b)

Fig. 8. Quantized video frame for $p_2 = 10^{-2}$. (a) Finer quantization—Missa frame no. 15, (b) coarser quantization—Missa frame no. 15.

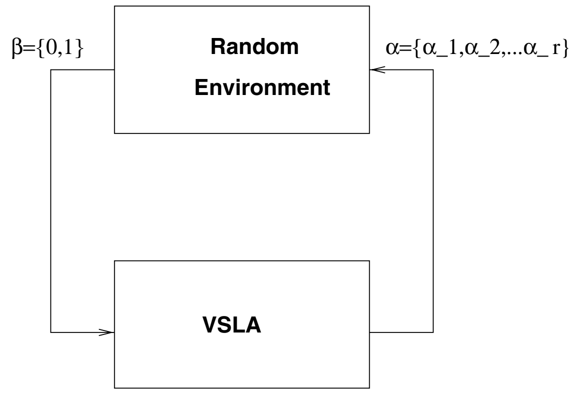

Fig. 9. Schematic of stochastic learning automaton.

its performance with time. This can be used to optimize functionals which may not be known completely.

A VSLA is described by a 5-tuple $\{\alpha, \beta, p, T, C\}$, where

- $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_r\}$ is the set of r actions from which the automaton can choose any action at time n denoted by $\alpha(n)$.
- $\beta = \{0, 1\}$ is the set of binary response to the VSLA from the environment for a chosen action; $\beta = 0$ is a reward and $\beta = 1$ corresponds to a penalty.
- $p = \{p_1, p_2, \ldots, p_r\}$ is the set of probabilities.
- T is the stochastic learning algorithm according to which the elements of the set p are updated at each time n, i.e., $p(n+1) = T[\alpha(n), \beta(n), p(n)]$, where the ith element of the set $p(n)$ is $p_i(n) = \Pr(\alpha(n) = \alpha_i)$, $i = 1, 2, \ldots, r$, $\sum_{i=1}^{r} p_i(n) = 1, \forall n$ and $p_i(1) = \frac{1}{r}, \forall i$.
- $C = \{c_1, c_2, \ldots, c_r\}$ is the set of penalty probabilities conditioned on the chosen action, where $c_i = \Pr(\beta = 1 | \alpha(n) = \alpha_i)$, $i = 1, 2, \ldots, r$.

The stationary random environment is represented by $C = \{c_1, c_2, \ldots, c_r\}$. The values of c_i are unknown and it is assumed that C has a unique minimum element. For a stationary random environment the penalty probabilities are constant. The working of the learning automaton can be described as follows. Initially at $n = 1$ one of the actions is chosen by the automaton at random with a given probability. This action is then applied to the system and the response from the environment is observed. If the response is favorable ($\beta = 0$) then the probability of choosing that action for the next period of time is updated according to the updating rule T. Then, another action is chosen and the response is observed. This process is repeated until a stopping criterion is reached. When the learning process stops the algorithm has learnt some characteristics of the random environment. In this paper, we consider the operator T to be linear. When T is the LRI algorithm it can be described by Narendra and Thathachar (1989)

$$\begin{aligned}
&\text{if } \beta_i(n) = 0 \\
&p_i(n+1) = p_i(n) + \sum_j (1-a) p_j(n); \quad \forall j, j \neq i \\
&p_j(n+1) = a p_j(n), \quad \forall j \neq i \\
&\text{if } \beta_i(n) = 1 \\
&p_i(n+1) = p_i(n), \quad \forall i
\end{aligned} \tag{3}$$

where $\beta_i(n)$ is the response when action i is chosen at time n and a is the *reward parameter*. The idea behind these update equations is that when a chosen action results in a reward the probability of choosing that action in the future is increased by a small amount and the other action probabilities are decreased. If a penalty is received then the probabilities are not updated. We now establish the theoretical basis of LRI. Let the average penalty received by the automaton be

$$\Psi(n) = E[\beta(n)|p(n)] = \sum_{i=1}^{r} c_i p_i(n) \tag{4}$$

where $E[\cdot]$ is the expectation operator.

Definition 1 (Narendra and Thathachar, 1989). A learning automaton is *absolutely expedient* if $E[\Psi(n+1)|p(n)] < \Psi(n)$, $\forall n$, $\forall p_i(n) \in (0,1)$ and for all possible c_i, $i = 1, 2, \ldots, r$.

This means that absolutely expedient learning results in a decreasing average penalty function.

Definition 2 (Narendra and Thathachar, 1989). A learning automaton is ϵ-*optimal* if $\lim_{n\to\infty} E[\Psi(n)] < \min_i \{c_i\} + \epsilon$ for any arbitrary $\epsilon > 0$.

That is, using ϵ-optimal learning we can obtain a solution whose cost is arbitrarily close to the optimal cost. It is shown in (Narendra and Thathachar, 1989) that the unit vectors in $\Re^r$ are absorbing states of the Markov process $\{p(n)\}$ for LRI learning. The process $\{p(n)\}$ gets absorbed w.p. l under certain conditions. From this we conclude that the learning process using LRI terminates w.p. l. Further, LRI is absolutely expedient and ϵ-optimal.

2.4. Joint rate control and channel estimation

Adaptive rate control is one way of achieving error-resilience. For channel matched source rate control the channel bit error probability needs to be estimated first. Transmitting pilot symbols to estimate p_e is a common solution. But, this introduces delay and costs bandwidth. We now discuss a way to overcome this problem by jointly controlling the rate of quantization and on-line estimation of p_e using VSLA. We assume that p_e can take only one of the three values, 10^{-1}, 10^{-2}, or 10^{-3}. At the beginning of the transmission the actual p_e for the channel is unknown. Now, let the set of actions of the automaton, $\alpha = \{\alpha_1, \alpha_2, \alpha_3\}$ correspond to the three channel matched empirically optimal quantizers for channel bit error rates 10^{-1}, 10^{-2}, and 10^{-3} respectively. Since there is a one-to-one correspondence between quantizers and the channel bit error probability, by learning the optimal quantization parameter we also estimate p_e. Let a favorable response ($\beta = 0$) from the decoder for a chosen quantizer imply that the PSNR of the current received video frame is greater than or equal to that of the previous frame and 1 is an unfavorable response. We assume here that PSNR and the number of blocks in error in the received frame are inversely proportional. Therefore, a high PSNR implies fewer number of blocks in error. The penalty probabilities for the choice of each action is unknown and defines the environment (channel's conditions). The goal is to maximize the PSNR of the received video signal by learning the channel condition and choosing the corresponding optimal rate for the source quantizer. This corresponds to learning the action with the minimum penalty probability. The probability of choosing the quantizers are updated using LRI. The typical steps involved in the proposed algorithm are as follows:

- I-frame is quantized using a high rate quantizer and transmitted with sufficient protection.
- The decoder, after reconstructing this frame, quantizes the frame using the quantization tables that have been empirically optimized for the three channel bit error probabilities and stores them in a buffer.
- The VSLA chooses a quantizer randomly for the nth frame with the given probability $\{p_1(n), p_2(n), p_3(n)\}$.
- The quantized frame is transmitted along with the the quantizer information as protected side information.
- A response β based on the PSNR of the decoded frame is transmitted as a feedback information.
- Based on this feedback the probabilities of choosing the quantizers for the $(n+1)$st frame is computed using LRI.
- The algorithm learns until the probability of choosing the optimal action for the unknown p_e converges to 1.

When the algorithm converges it has learnt the unknown p_e of the channel by the optimal choice of the quantizer factor. Of course, this method could result in the first few frames to be sub-optimally quantized. This is the cost incurred in on-line channel estimation. However, the learning delay can be controlled by the value of the reward parameter. Depending on the value of the error tolerance ϵ a suitable reward parameter can be chosen. A higher reward parameter results in faster convergence of the LRI learning. Since $p(n)$ converge w.p. l let $\lim_{n\to\infty} \Psi(n) = \Psi^*$ w.p. l. Then, the average rate of convergence of LRI learning is (Narendra and Thathachar, 1989) $\rho_{av} \approx \frac{E[\Psi(n+1)-\Psi^*]}{E[\Psi(n)-\Psi^*]}$. After every frame n, $E[\Psi(n) - \Psi^*]$ decreases by a factor of ρ_{av}. If $\widetilde{T}$ is the time taken for

$E[\Psi(0) - \Psi^*]$ to decrease to d times its value, then $\widetilde{T} = \log d / \log \rho_{av}$. For slowly changing channels, if the channel bit error probability changes then the encoder will receive a series of penalties. Then the learning process can be started again. Therefore, the encoder is in sync with the channel again.

3. Performance analysis

In this section we discuss the performance of the adaptive quantizer and on-line channel estimator. The H.261 video codec used for experiments was implemented in C by the authors and their students. Results are presented for the standard grey level, qcif format, Miss America video sequence at 10 frames/s. The uncompressed bit rate was about 2 Mbps and the highest compressed video sequence had a rate of 35 Kbps for a particular choice of the quantization factor given in the following experimental results. Before we present the experimental results we make note of some points on the advantage of the proposed joint rate control and channel estimation technique with regards to transmission power savings and channel capacity usage. In the proposed scheme only one bit feed back is assumed. This significantly reduces the feed back channel requirement and thus enhances the reverse channel capacity. Feed back channel transmission power requirement is also reduced. This could be useful in uplink communications when mobile devices are battery power limited. As as aside, we note that many wireless systems use several bits of feed back for rate control as against the one bit feed back in the algorithm presented in this paper. Also, since the proposed algorithms does not need a pilot channel for wireless link state estimation, the transmission power used for this channel is saved. This savings could be significant (in 3G systems up to 25% of total transmitted power is used in pilot signaling).

Figs. 10–12 show the convergence of the linear LRI learning to the optimal quantizer when $p_e = 10^{-1}$. It is seen that $p_1(n)$ corresponding to the optimal quantizer converges to 1 and $p_2(n)$ and $p_3(n)$ converge to zero for all the three sequences. Both $p_2(n)$ and $p_3(n)$ have the same behavior as n varies. We also observe that increasing the value of the reward parameter results in a faster learning. We find similar convergence results for other bit error probabilities and other video sequences too.

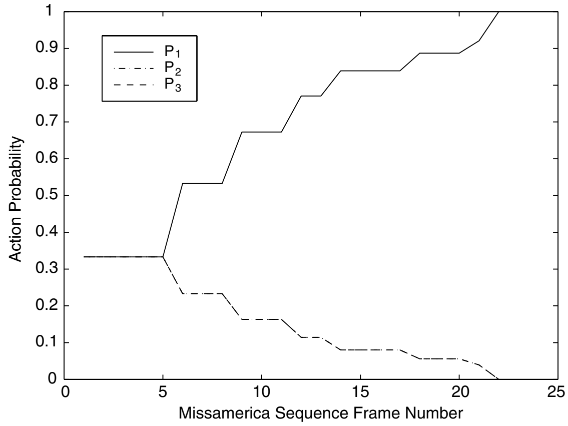

Fig. 10. Miss America sequence, $a = 0.3$.

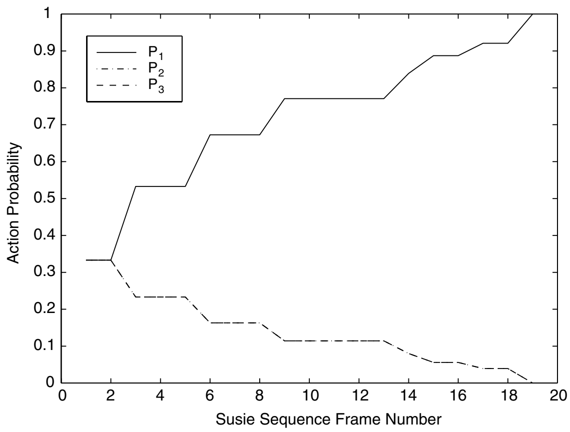

Fig. 11. Susie sequence, $a = 0.3$.

Fig. 13 shows the reconstructed frames of the Miss America sequence when $p_e = 10^{-1}$. Clearly, the optimal quantizer when $M = 2$ results in a decrease in the number of corrupted blocks. A similar behavior is seen in Fig. 14 when $p_2 = 10^{-2}$. This performance can be further enhanced by using additional error protection. Fig. 15 shows the trajectory of PSNR using the adaptive learning rate control algorithm when the average rate was 1 Mbps. Here, 125 frames of the Miss America sequence was used and the channel bit error rate

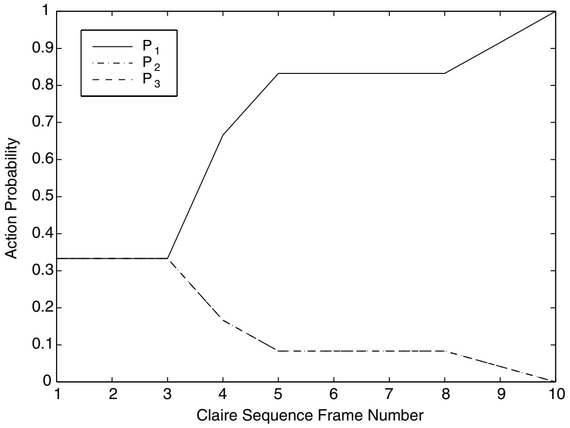

Fig. 12. Claire sequence, $a = 0.5$.

was allowed to change from 10^{-2} to 10^{-1}. The learning parameter $a = 0.3$ was chosen. We see from the figure that during the channel transition period (at the 50th frame) the rate controller senses the change and starts searching the space of empirically optimized quantizers. This search continues for nearly 14 frames when the right quantizer is obtained with a high probability. The performance at the decoder during these 14 frames fluctuates as seen in Fig. 15. Similar performances have been observed for other video sequences. Clearly, there is an important related question here: how often to trigger the learning algorithm in a dynamically changing wireless environment? Unfortunately this question does not have a straightforward answer. However, there is a clear trade-off here. Consider the two cases: (a) the channel has changed *significantly* and the learning algorithm has not been triggered and (b) learning algorithm has been triggered erroneously. In the first case, suppose the channel has changed from a higher bit error rate to a lower one, then, by not triggering the learning algorithm to compute the new (higher) source coding rate, the source coder induced distortion at the receiver will be high. On the other hand, if the channel has changed from a lower bit error rate to higher, then the channel induced distortion will be larger. In case (b), the loss will be in terms of PSNR during the learning period when the quantizer randomly tries different quantization parameters. One way to alleviate this problem would be not to rely only upon physical layer information but also use information from higher layers of the protocol stack.

4. Conclusion

A joint adaptive rate control and channel estimation algorithm based on stochastic learning is presented. First, channel-matched quantizer design is discussed. The quantizers are optimized

(a) (b)

Fig. 13. Reconstructed Miss America frames for $p_e = 10^{-1}$. (a) Frame 15, $M = 1.3$, (b) frame 15, $M = 2.0$.

(a) (b)

Fig. 14. Reconstructed Miss America frames for $p_e = 10^{-2}$. (a) Frame 25, $M = 1.3$, (b) frame 25, $M = 2.0$.

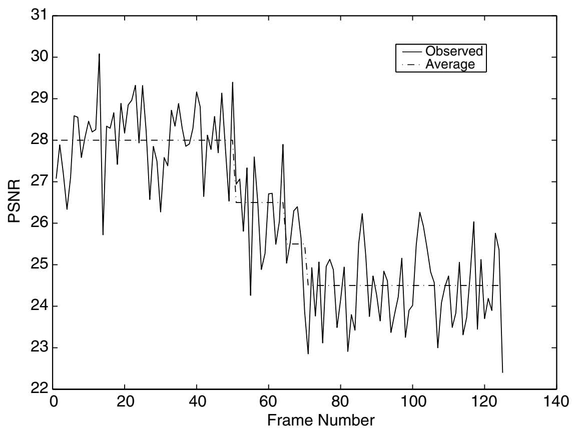

Fig. 15. Adaptive learning rate control for Miss America sequence, $a = 0.3$.

empirically based on simulation data. The application of LRI learning to source rate control for video transmission is studied. Some convergence properties of this method are analyzed. The convergence of the algorithm to the optimal channel matched quantizer is fast. The learning delay and optimal quantization can be traded-off using the learning parameter. Simulation results are given for different channel bit error probabilities and for various video sequences. The delay in the existing schemes that employ pilot signaling for channel identification before transmission is avoided in this method thus enabling on-line rate control. The PSNR of the received video signal is shown to be better using the proposed approach. Finally, we note that this method is suitable for low power wireless video applications.

Acknowledgements

This work was partially supported by grants NSF ITR-0082064, NSF CAREER ANI 0133761, and Stevens Center for Wireless Network Security. The authors thank the editors for their comments that helped to improve the presentation of this paper. The authors also thank S. Kumar and Q. Chen for their help.

References

Alajaji, F., Fuja, T., 1994. A communication channel modeled on contagion. IEEE Trans. Inform. Theory 40, 2035–2041.

Alajaji, F., Farvardin, N., Fuja, T., 1996. Detection of binary Markov sources over channels with additive Markov noise. IEEE Trans. Inform. Theory 42, 230–239.

Bauer, R., Hagenauer, J., 2000a. Symbol by symbol MAP decoding of variable length codes. 3rd ITG Conference Source and Channel Coding.

Bauer, R., Hagenauer, J., 2000b. Iterative source/channel-decoding using reversible variable length codes. IEEE Data Compression Conference, pp. 93–102.

Bhaskaran, V., Konstantinides, K., 1995. Image and Video Compression Standard. Kluwer Academic Publishers.

Borko, J., Westwater, R., 1997. Motion Compensation Algorithms for Video Compression Standard. Kluwer Academic Publishers.

Burlina, P., Alajaji, F., 1998. An error resilient scheme for image transmission over noisy channels with memory. IEEE Trans. Image Process. 7, 593–600.

Bystrom, M., Modestino, J.W., 1998. Combined source–channel coding for transmission of H.263 coded video with trellis-coded modulation over a slow fading Rician channel. IEEE International Symposium on Information Theory, p. 12.

Bystrom, M., Kaiser, S., Kopansky, A., 2001. Soft source decoding with applications. IEEE Trans. Circuits Syst. Video Technol. 11, 1108–1120.

Cavers, J., 1991. An analysis of pilot symbol assisted modulation for rayleigh fading channels. IEEE Trans. Vehicular Technol. 40, 686–693.

Chandramouli, R., Kumar, S., Ranganathan, N., 1998a. Joint optimization of quantization and on-line channel estimation for low bit-rate video transmission. Proc. IEEE Int. Conf. Image Process. 1, 649–653.

Chandramouli, R., Ranganathan, N., Ramadoss, S., 1998b. Error resilient coding for jpeg image transmission over wireless fading channels. Proceedings of IEEE International Symposium on Circuits and Systems.

Chandramouli, R., Ranganathan, N., Ramadoss, S., 1998c. Adaptive quantization and fast error resilient entropy coding for image transmission. IEEE Trans. Circuits Syst. Video Technol. 8, 411–421.

Chen, Q., Subbalakshmi, K.P., 2003. Trellis decoding for MPEG-4 streams over wireless channels. SPIE Electr. Imaging: Image Video Commun. Process., 810–819.

Cheung, G., Zakhor, A., 2000. Bit allocation for joint source/channel coding of scalable video. IEEE Trans. Image Process. 9, 340–356.

Demir, N., Sayood, K., 1998. Joint source/channel coding for variable length codes. IEEE Data Compression Conference, pp. 139–148.

Dunham, J.G., Gray, R.M., 1981. Joint source and noisy channel trellis encoding. IEEE Trans. Inform. Theory 27, 516–519.

Fano, R., 1963. A heuristic discussion of probabilistic decoding. IEEE Trans. Inform. Theory 9.

Farvardin, N., 1990. A study of vector quantization for noisy channels. IEEE Trans. Inform. Theory 36, 799–809.

Guivarch, L., Carlach, J.-C., Siohan, P. 2000. Joint source–channel soft decoding of Huffman codes with turbo-codes. Data Compression Conference, pp. 83–92.

Hedayat, A., Nosratinia, A., 2002. On joint iterative decoding of variable-length codes and channel codes. IEEE Conference on Communications, Control, and Computing.

Hochwald, B., Zeger, K., 1997. Tradeoff between source and channel coding. IEEE Trans. Inform. Theory, 1412–1424.

Kliewer, J., Thobaben, R., 2002. Combining FEC and optimal soft-input source decoding for the reliable transmission of correlated variable-length encoded signals. IEEE Data Compression Conference, pp. 83–91.

Kopansky, A., Bystrom, M., 1999. Sequential decoding of MPEG-4 coded bitstreams for error resilience. The 33rd Annual Conference on Information Sciences and Systems.

Kurtenbach, A., Wintz, P., 1969. Quantization for noisy channels. IEEE Trans. Commun. Tech. 17, 291–302.

Lakovic, K., Villasenor, J., 2002. Combining variable length codes and turbo codes. IEEE Vehicular Technology Conference, pp. 1719–1723.

Lakovic, K., Villasenor, J., Wesel, R., 1999. Robust joint Huffman and convolutional decoding. IEEE Vehicular Technology Conference, pp. 2551–2555.

Murad, A.H., Fuja, T.E., 1998a. Joint source–channel decoding of variable-length encoded sources. IEEE Information Theory and Workshop.

Murad, A.H., Fuja, T.E., 1998b. Exploiting the residual redundancy in motion estimation vectors to improve the quality of compressed video transmitted over noisy channels. Proceedings of International Conference on Image Processing.

Narendra, K., Thathachar, M., 1989. Learning Automata: An Introduction. Prentice Hall.

Park, M., Miller, D.J., 1997. Low-delay optimal MAP state estimation in HMMS with application to symbol decoding. IEEE Signal Process. Lett. 4, 289–292.

Park, M., Miller, D.J., 2000. Joint source–channel decoding for variable-length encoded data by exact and approximate MAP sequence estimation. IEEE Trans. Commun. 48, 1–6.

Phamdo, N., Farvardin, N., 1994. Optimal detection of discrete Markov sources over discrete memoryless channels. IEEE Trans. Inform. Theory 40, 186–193.

Phamdo, N., Alajaji, F., Farvardin, N., 1997. Quantization of memoryless and Gauss–Markov sources over binary Markov channels. IEEE Trans. Commun. 45, 668–674.

Sayood, K., Borkenhagen, J.C., 1991. Use of residual redundancy in the design of joint source channel coders. IEEE Trans. Commun. 39, 839–846.

Sayood, K., Liu, F., Gibson, J.D., 1994. A constrained joint source/channel coder design. IEEE Trans. Commun. 12, 1584–1593.

Shannon, C., 1949. The mathematical theory of communication. Bell Syst. Tech. J. 28, 379–423.

Subbalakshmi, K.P., Chen, Q., 2002. Joint source–channel decoding for MPEG-4 coded video over wireless channels. IASTED International Conference on Wireless and Optical Communications, pp. 617–622.

Subbalakshmi, K.P., Vaisey, J., 1998. Optimal decoding of entropy coded memoryless sources over binary symmetric channels. IEEE Data Compression Conference, p. 573.

Subbalakshmi, K.P., Vaisey, J., 1999a. Joint source–channel decoding of entropy coded Markov sources over binary symmetric channels. IEEE International Conference on Communications, vol. 1, pp. 446–450.

Subbalakshmi, K.P., Vaisey, J., 1999b. Optimal decoding of entropy coded Markov sources over channels with memory. The 33rd Annual Conference on Information Sciences and Systems, vol. 2, pp. 624–629.

Subbalakshmi, K.P., Vaisey, J., 2001. On the joint source–channel decoding of variable-length encoded sources: the BSC case. IEEE Trans. Commun. 49, 2052–2055.

Subbalakshmi, K.P., Vaisey, J., in press. On the joint source–channel decoding of variable-length encoded sources: The additive markov channel case. IEEE Trans. Commun.

Vembu, S., Verdu, S., Steinberg, Y., 1995. The source–channel separation theorem revisited. IEEE Trans. Inform. Theory 41, 44–54.

Wen, J., Villasenor, J.D., 1999. Utilizing soft information in decoding of variable length codes. Data Compression Conference, pp. 131–139.