Adaptive Critic Design for Energy Minimization of Portable Video Communication Devices

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***Abstract*—Portable video communication devices operate on batteries with limited energy supply. However, video compression is computationally intensive and energy-demanding. Therefore, one of the central challenging issues in portable video communication system design is to minimize the energy consumption of video encoding so as to prolong the operational lifetime of portable video devices. In this work, we consider a video encoder as a nonlinear system with a number of encoder parameters to its power consumption. We explore the approach of adaptive critic design to control and optimize the power consumption behavior of a portable video encoding system. Our experimental results demonstrate that this approach is very efficiently, being able to achieve the optimum performance accurately and robustly.**

Keywords- video compression, energy minimization, adaptive control, optimization.

I. INTRODUCTION

PORTABLE devices are powered by batteries. Video encoding schemes are still computationally intensive and energy-demanding, even after being fully optimized with existing software and hardware energy-minimization techniques [1, 4, 8]. As a result, the operational lifetime of current portable video systems, such as handheld video devices, is still very short, mostly in the range of a few hours. This has become a bottleneck issue for technological progress in portable video electronics.

In the age of desktop computing and wired communication, people worried about bits, storage space or transmission bandwidth. To analyze, model, control, and optimize the performance of a signal processing and communication system under bit rate constraints, rate-distortion (R-D) theories and algorithms have been developed [10]. With recent technological advances in circuit design and wireless communication, the storage space and network bandwidth have experienced dramatic growth, being improved by hundreds of times during the past decade. Currently, in many portable communication applications, energy has become a much more scarce and critical resource than bits [8]. Therefore, how to incorporate the energy consumption into the existing R-D performance analysis framework so as to optimize the communication system performance under bit and energy constraints emerges as a new research issue.

There are two types of portable video devices: encoder (e.g., video cell phones, wireless video cameras, etc) and player (e.g., iPod video). In this work, we focus on energy minimization for portable video encoding devices. This is because, on portable video devices, the fraction of energy consumption by video encoding (typically 60-85%) is much higher than that of video decoding. To reduce the energy consumption of video encoders, a lot of algorithms, software and hardware energy-minimization techniques, including low-complexity encoder design, low-power embedded video encoding, adaptive power control, and joint encoder and hardware adaptation have been developed [1, 4, 8, 9]. These algorithms focus on encoder complexity (and power consumption) reduction through heuristic adaptation or control instead of systematic energy optimization.

In this work, we propose to develop a systematic approach to control and optimize the energy consumption behavior of portable video encoding devices using adaptive critic design [6]. More specifically, we consider the video encoder as a nonlinear dynamic system. The purpose of energy consumption control is to find a sequence of encoding parameters such that the overall energy consumption is minimized under the rate-distortion constraints. Our experimental results demonstrate that this nonlinear system control approach is very effective, being able to achieve the optimum performance.

The rest of the paper is organized as follows. In Section II, we discuss energy-scalable video encoding system design. Section III presents our adaptive critic system design. Section IV presents the experimental results on energy consumption control and optimization in real-time video encoding. Section V concludes the paper.

II. OPERATIONAL POWER-RATE-DISTORTION ANALYSIS

In this section, we study the energy consumption behavior of a video encoder and introduce the operational power-rate-distortion (P-R-D) analysis. The operational P-R-D analysis will be performed offline and provide the ground-truth optimum performance which will be used for performance evaluation of the proposed algorithm.

The central task of P-R-D analysis is to answer the following question [1]: *what is the minimum video distortion (or equivalently, video quality) that a video encoder can* *achieve under bit rate and power consumption constraints*?

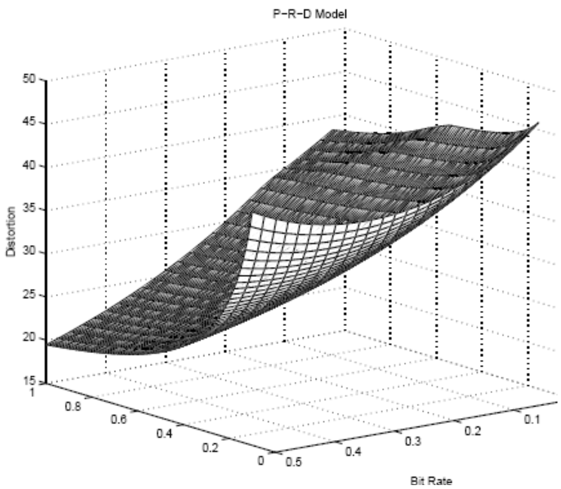

Figure 1. P-R-D function.

Our central idea is to introduce a set of complexity control parameters to control (scale down) the computational complexity of major encoding operations of the video encoder. With DVS (Dynamic Voltage Scaling), a recently developed power control technology for microprocessors [3], this complexity-scalable video encoder can be translated into an energy-scalable video encoder. More specifically, the energy-scalable video encoder design has the following three major steps.

In the first step, we group the encoding operations into several modules, such as motion prediction, pre-coding (transform and quantization), and entropy coding, and then introduce a set of control parameters $\Gamma = [\gamma_1, \gamma_2, ...\gamma_L]$ to control the power consumption of these modules. Therefore, the encoder complexity C is then a function of these control parameters, denoted by $C(\gamma_1, \gamma_2, ...\gamma_L)$. Within the DVS design framework, the encoding power consumption, denoted by P, is a function of encoder complexity C, therefore, also a function of $\Gamma = [\gamma_1, \gamma_2, ...\gamma_L]$, denoted by $P(\gamma_1, \gamma_2, ...\gamma_L)$. The expression of this function also depends on the power consumption model of the specific micro-processor.

In the third step, either experimentally or analytically, we study the R-D behavior of each control parameter, and integrate these models into a comprehensive parametric R-D model for the video encoder, denoted by $D(R; \gamma_1, \gamma_2, ...\gamma_L)$. We perform optimum configuration of the control parameters to maximize the video quality (or minimize the video distortion) under the power constraint. This optimization problem can be mathematically formulated as follows:

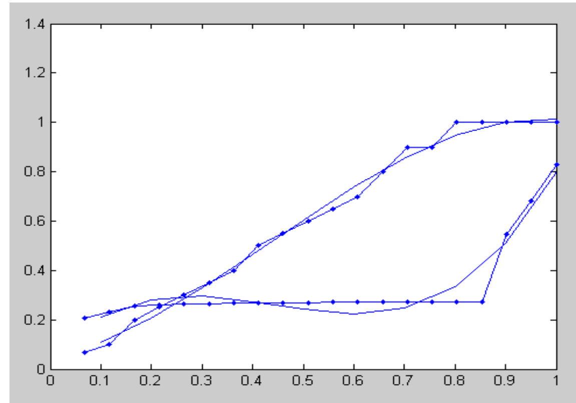

Figure 2: optimum encoder control parameters.

$$\min_{\{\gamma_1, \gamma_2, ...\gamma_L\}} D = D(R; \gamma_1, \gamma_2, ...\gamma_L),$$
$$s.t. \quad P(\gamma_1, \gamma_2, ...\gamma_L) \le P \quad (1)$$

where P is the available power consumption for video encoding. The optimum solution, denoted by $D(R; P)$, describes the P-R-D behavior of the video encoder.

To view the P-R-D model in more detail, we plot the D-P curves for different bit rates, ranging from 0.01 bpp (bits per pixel) to 1.0 bpp in Fig.1. Fig.2 shows the D-P curves at different bit rates R_s. Fig. 3 shows the optimum complexity control parameters. We can see that when the power supply level is low, the $D(R)$ function is almost flat, which means the video processing and encoding efficiency is very low; hence, in this case, more bandwidth does not improve the video presentation quality. The P-R-D model has direct applications in energy management, resource allocation, and QoS provisioning in wireless video communication, especially over wireless video sensor networks.

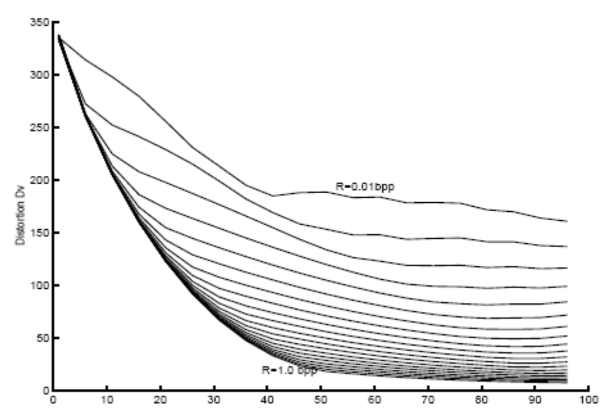

Figure 3: P-R-D function.

III. ADAPTIVE CRITIC DESIGN FOR ENERGY CONTROL AND OPTIMIZATION

It should be noted that the operational P-R-D analysis proposed in the previous section involves very high computational complexity. It is intended for offline modeling and analysis only and not suitable for real-time energy consumption control and optimization. In this work, based on the action-dependent and globalized dual heuristic dynamic programming (ADGDHP) method, we designed an optimal controller for real-time energy consumption control and optimization [6, 7].

The adaptation in ADGDHP is shown in Fig. 4. It consists of three major components: a model network, a critic network, and an action network. The inputs to the model network are system state variable $X(k)=[D(k)\ P(k)\,R]^T$ and encoder control parameters $A(k)=[A_1(k)\ A_2(k)\ A_3(k)]^T$. Here $D(k)$ and P(k) are video coding distortion and encoding power consumption at time (or frame) k.
We assume a rate control algorithm operates inside the encoder such that the encoding bit rate R remains relatively constant throughout the process. In this work, we set $A(k)=[A_1(k)\ A_2(k)\ A_3(k)]^T$ to be the complexity control parameters $\Gamma=[\gamma_1,\gamma_2,....\gamma_L]$. The output of the model network is the system state at the next time instance. The task of the critic network is to learn the cost-to-go performance metric function $J(k)$, while the action network will determine the encoder control parameters $A(k)=[A_1(k)\ A_2(k)\ A_3(k)]^T$ to minimize $J(k)$. In the following, we will discuss detailed design of these three networks.

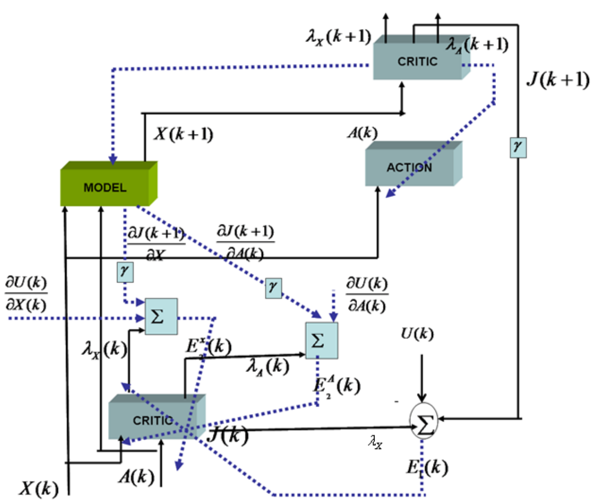

Figure 4: block diagram of the proposed ADGDHP design for energy consumption control and optimization.

A. *Critic Network Design*

Dynamic programming is a general approach for sequential optimization applicable under very broad conditions. Fundamental to this approach is Bellman Principle of Optimality [5]: if a trajectory of actions is optimum, no matter how an intermediate point is reached, the rest of the trajectory must coincide with an optimal trajectory as calculated with the intermediate point as the starting point. This principle is applied by formulating a "primary" utility function $U(t)$ that represents a control objective for a particular context in one or more measurable variables. A secondary utility function is then formed:

$$J(t)=\sum_{k=0}^{\infty}\gamma^K U(t+k) \tag{2}$$

Unfortunately, minimization of $J(t)$ is not computationally tractable for most real applications. Instead, the Bellman recursion is often used:

$$J(t)=U(t)+\gamma J(t+1) \tag{3}$$

where γ is a discount factor for finite horizon problems (0 < r < 1) and $U(t)$ is the utility function or local cost.A critic neural network shown in Fig.5 is used to estimate $J(t)$. Here we chose 3 hidden neuron, thus i=1, 2, 3 with weights

$$w_i^C=[w_{i0}^C\ \ w_{i1}^C\ \ w_{i2}^C\ \ w_{i3}^C\ \ w_{i4}^C\ \ w_{i5}^C\ \ w_{i6}^C](i=1,2,3)$$

$V^C=\left[V_0^C\ \ V_1^C\ V_2^C\ \ V_3^C\right]^T$ is the weight of the output neuron. In this neural network, we have:

$$\begin{aligned} q_i &= [1\ \mathrm{D}\ \mathrm{P}\ \ \mathrm{R}\ \ \mathrm{A}_1\ \ \mathrm{A}_2\ \ \mathrm{A}_3\,]W_i^C \\ S_i &= \sigma(q_i)=\frac{1}{1+e^{-q_i}} \\ J &= [1\ \ S_1\ S_2\ \ S_3]V^C \end{aligned} \tag{4}$$

The critic NN outputs the scalar J and two vectors, $\lambda_X(k+1)$ and $\lambda_A(k+1)$. J is the cost function, estimated as:

$$J(k)=\sum_{i=1}^{hc}V_{ci}(k)S_i(k),\ where\ \ S_i(k)=\sigma(q_i(k))=\frac{1}{1+e^{-q_i(k)}},q_i(k)=\sum_{j=0}^{6}w_{ij}^C(k)I_j^C(k),\ (I_0^C(k)=1)$$

$$\begin{aligned} \lambda_X &= [\lambda_{X_1}\ \ \lambda_{X_2}\ \ \lambda_{X_3}]=[\lambda_D\ \ \lambda_P\ \ \lambda_R],\ \ whrere\ \lambda_{X_i}(k+1)=\frac{\partial J(k+1)}{\partial_{X_i}(k+1)} \\ \lambda_A &= [\lambda_{A_1}\ \ \lambda_{A_2}\ \ \lambda_{A_3}],\ where\ \lambda_{A_i}(k+1)=\frac{\partial J(k+1)}{\partial_{A_i}(k+1)} \end{aligned} \tag{5}$$

It should be noted that, in action dependent forms of ACD's, we have

$$\begin{aligned} \frac{\partial J(k+1)}{\partial A_l(k)} &= \sum_{i=1}^{n}\lambda_{X_i}(k+1)\frac{\partial X_i(k+1)}{\partial A_l(k)} \\ \frac{\partial J(k+1)}{\partial X_j(k)} &= \sum_{i=1}^{n}\lambda_{X_i}(k+1)\frac{\partial X_i(k+1)}{\partial X_j(k)}+\sum_{l=1}^{m}\lambda^*{}_{A_l}(k)\frac{\partial A_l(k)}{\partial X_j(k)} \end{aligned} \tag{6}$$

where

$$\lambda^*{}_{A_l}(k)=\frac{\partial J(k+1)}{\partial A_l(k)}+\frac{\partial U(k)}{\partial A_l(k)} \tag{7}$$

n, m are the dimension of the output of the model and the action networks, respectively. The critic network tries to minimize the following error measure over time:

$$E^C=\sum_k E_1^2(k)+\sum_k E_R{}^T(k)E_R(k)+\sum_k E_A{}^T(k)E_A(k)$$

where

$$
\begin{aligned}
E^C &= \sum_k E_1^2(k) + \sum_k E_2^{xT}(k) E_2^x(k) + \sum_k E_2^{AT}(k) E_2^A(k) \quad , \\
E_1(k) &= J(k) - \gamma J(k+1) - U(k) \\
E_{2\,j}^x(k) &= \frac{\partial J(k)}{\partial X_j(k)} - \gamma \frac{\partial J(k+1)}{\partial X_j(k)} - \frac{\partial U(k)}{\partial X_j(k)} \qquad (E_2^x(k) \in R^n) \\
E_{2\,l}^A(k) &= \frac{\partial J(k)}{\partial A_l(k)} - \gamma \frac{\partial J(k+1)}{\partial A_l(k)} - \frac{\partial U(k)}{\partial A_l(k)} \qquad (E_2^A(k) \in R^m)
\end{aligned}
$$

γ is the discount factor ($0 < \gamma < 1$). We apply the LMS algorithm and it results in an update rule as below:

$$\Delta w_{ji}^C = -\eta_1 E_1(k) \frac{\partial J(k)}{\partial w_{ji}^C} - \eta_2 \sum_{s=1}^{n} [\frac{\partial J(k)}{\partial X_s(k)} - \gamma \frac{\partial J(k+1)}{\partial X_s(k)} - \frac{\partial U(k)}{\partial X_s(k)}] \frac{\partial^2 J(k)}{\partial X_s \partial w_{ji}^C} + \eta_3 \sum_{t=1}^{m} [\frac{\partial J(k)}{\partial A_t(k)} - \gamma \frac{\partial J(k+1)}{\partial A_t(k)} - \frac{\partial U(k)}{\partial A_t(k)}] \frac{\partial^2 J(k)}{\partial A_t \partial w_{ji}^C}$$

η_1, η_2, η_3 are three positive learning rates with respect to the three tuning paths in Fig. 3.

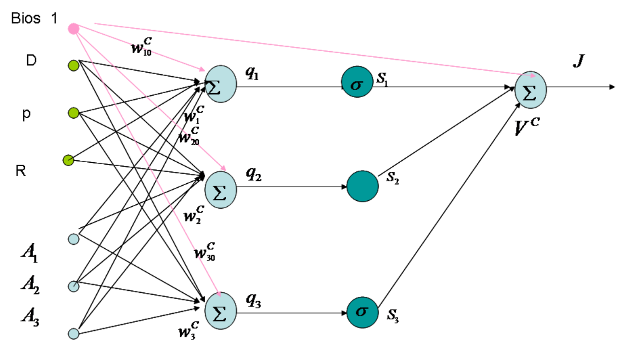

Figure 5: Critic neural network.

B. Action Network Design

The action NN has a similar structure as that of the critic NN. Fig. 5 also shows the direct adaptation path $\lambda_A(k+1)$ between the action and the critic networks. The goal of action's training is to make $\lambda_A(t)$, the derivative of $J(t)$ with respect to the action, to approach zero. To train the action network, we use only the critic's $\partial J / \partial A$ outputs so as to meet the equation above. Thus, the error in action is:

$$E = \lambda_A^T(k+1)\lambda_A(k+1) \qquad (5)$$

The input of action NN is the state vector *X,* and the output is the control or action vector *A*. The weight update rule can me simply expressed as follow:

$$\Delta W^A = -\eta^A [\lambda_A(k+1)]^T \frac{\partial A(k)}{\partial W^A} \qquad (6)$$

where η^A is a positive learning rate of the action NN.

C. Model Neural Network Design

The objective of model NN is to predict the next system state $X(k+1)$ for given current system state $X(k)$ and action vector (or encoder control parameters) $A(k)$. To do this, we also use the neural network shown in Fig. 5. In video encoding, we are able to directly measure the system state variables. Let

$$Y(k+1) = [D(k+1), P(k+1), R(k+1)] \qquad (7)$$

be the measured system state variables, namely, the encoded video quality $D(k+1)$, encoding bit rate $R(k+1)$, and encoding power $P(k+1)$. Then the error in modeling is given by

$$E = [Y(k+1) - X(k+1)]^T [Y(k+1) - X(k+1)] \qquad (8)$$

which can be used to tune the weights of the model neural network.

IV. Energy Consumption Control and Optimization for Real-Time Video Encoding

In video encoding, there are three computationally intensive operations, namely, motion estimation, pre-coding, and entropy coding. All of these operations are performed on a block basis. In this work, we use three encoder complexity control parameters $A(k) = [A_1(k)\ A_2(k)\ A_3(k)]^T$, where $A_1(k)$ is the number of SAD (sum of absolute difference) computations used in motion search; $A_2(k)$ is the number of skipped blocks; $A_3(k)$ is the frame rate. Here, k represents the frame number.

The model is trained offline with training sequences. In this work, we use 6 training video sequences, all in QCIF (176x144) size encoded by MPEG-4 video encoder at 15 frames per second. The proposed ADGDHP approach for energy consumption control operates at video frame level. The objective is to minimize the overall video distortion under the energy constraint.

We choose two test QCIF video sequences, Carphone and Coastgurad, shown in Fig. 6 to evaluate the proposed approach. Each sequence has 300 frames. Fig. 7 shows the average video distortion (dotted lines) achieved by the proposed approach on Carphone. It also shows in solid lines the ground truth optimum obtained by operational P-R-D analysis. The result for Coastguard is shown in Fig. 8. It can be seen that the performance gap between them is very small. This indicates that the proposed approach for real-time energy consumption control and optimization is very effective.

V.

VI. Conclusion

Energy consumption control and optimization for real-time video encoding over portable video communication devices is a very challenging task since the encoder is highly nonlinear with very complex energy consumption behaviors. Operational P-R-D analysis is too computationally intensive and is not suitable for real-time application. In this work, we have developed an adaptive critic design approach for energy consumption control and optimization. Our experimental results demonstrate that this approach is very efficiently, being able to achieve the optimum performance accurately and robustly.

Figure 6: test video clips: Carphone and Coastguard.

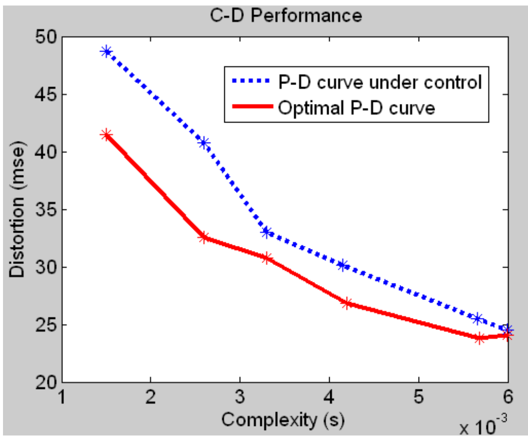

Figure 7: Energy consumption control result and the ground-truth optimum on Carphone video.

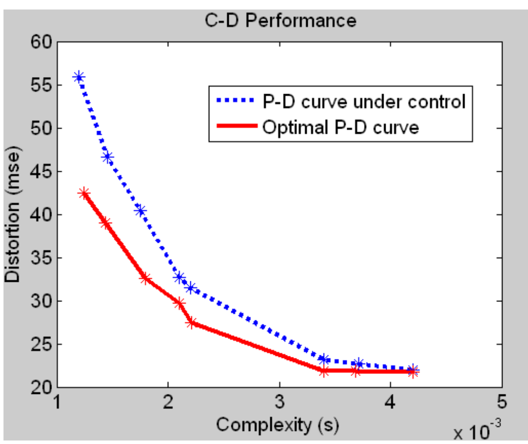

Figure 8: Energy consumption control result and the ground-truth optimum on Coastguard video.

Acknowledgement

This work has been supported in part by NSF under grant DBI-0529082.

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