Rate-Distortion Optimal Bit Allocation for Object-Based Video Coding

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***Abstract*—In object-based video encoding, the encoding of the video data is decoupled into the encoding of shape, motion, and texture information, which enables certain functionalities, like content-based interactivity and content-based scalability. The fundamental problem, however, of how to jointly encode this separate information to reach the best coding efficiency has not been studied thoroughly. In this paper, we present an operational rate-distortion optimal scheme for the allocation of bits among shape, motion, and texture in object-based video encoding. Our approach is based on Lagrangian relaxation and dynamic programming. We implement our algorithm on the MPEG-4 video verification model, although it is applicable to any object-based video encoding scheme. The performance is accessed utilizing a proposed metric that jointly captures the distortion due to the encoding of the shape and texture. Experimental results demonstrate that the gains of lossy shape encoding depend on the percentage the shape bits occupy out of the total bit budget. This gain may be small or may be realized at very low bit rates for certain typical scenes.**

***Index Terms*—MPEG-4, object-based video, rate-distortion, shape coding, video coding.**

I. Introduction

In RECENT years, object-based video coding has become one of the most important topics in the visual communication field, along with the development of new functions for modern interactive multimedia applications. The MPEG-4 standard [1] was developed as the first international multimedia standard that addresses object-based video representation. The central concept in MPEG-4 is that of the video object (VO), which is characterized by intrinsic properties such as shape, texture, and motion. For each arbitrarily shaped VO, each frame of a VO is called a VO plane (VOP). The VOP encoder essentially consists of separate encoding schemes for shape and texture. The purpose of the use of shape is to achieve better subjective picture quality, increased coding efficiency, as well as, object-based video representation and interactivity. The shape information for a VOP, also referred to as an alpha-plane, is specified by a binary array corresponding to the rectangular bounding box of the VOP specifying whether an input pixel belongs to the VOP or not, or a set of transparency values ranging from 0 (completely transparent) to 255 (opaque). In this paper, only a binary alpha plane is considered, although the proposed algorithm can be extended to the grayscale alpha plane cases. The texture information for a VOP is available in the form of a luminance (Y) and two chrominance (U,V) components. It is important to point out that the standard does not describe the method for creating VOs, that is, they may be created in various ways depending on the application.

In object-based video compression, the optimal allocation of bits among shape, texture and motion is a fundamental problem. The difficulty of this optimal bit allocation problem is due to the dependencies between shape and texture of an object, as well as, the dependencies at the macroblock level due to motion compensated predictive coding and differential encoding.

Shape and texture have been jointly considered in object boundary encoding and rate control. In [2] and [3], vertex based boundary encoding is considered utilizing an adaptive distortion metric which is based on texture information. More specifically, texture gradient information determines the local degree of trust in the accuracy of the shape information and subsequently the allocation of bits in encoding the boundary (i.e., more bits are allocated to the encoding of the parts of the boundary which are trusted more). In [4]–[6], adaptive shape-coding control mechanisms are proposed to provide a tradeoff between texture and shape coding accuracy. The shape threshold value, Alpha_TH, which controls the accuracy of the encoded shape, is set adaptively based on previous coding information, thus balancing the bit allocation without introducing excessive distortion. The adjustment of Alpha_TH is mainly based on the number of frames skipped (as indicated by the value of FrameSkip) at a given time instant and a skip threshold (Skip_TH). For example, if FrameSkip $>$ Skip_TH, Alpha_TH is increased, resulting in the allocation of fewer bits and, therefore, a coarser shape approximation for the next frame. Otherwise, Alpha_TH is reduced, resulting in a better shape approximation for the next frame. In these schemes, however, the distortion from the encoding of shape and texture is neither explicitly nor jointly studied, and the use of Alpha_TH, may not affect the shape approximation as much as expected. So far, none of these approaches provides a rate distortion optimal bit allocation.

In this paper, we propose an operational rate-distortion optimal bit allocation scheme for object-based video coding. The algorithm is based on Lagrangian relaxation and dynamic programming. We implemented our scheme on the MPEG-4 verification model. It is important to point out that we are not proposing an optimal rate control mechanism; instead we assume there is a rate controller available to assign the bit budget for each frame (or VOP for MPEG-4), or that, as a special

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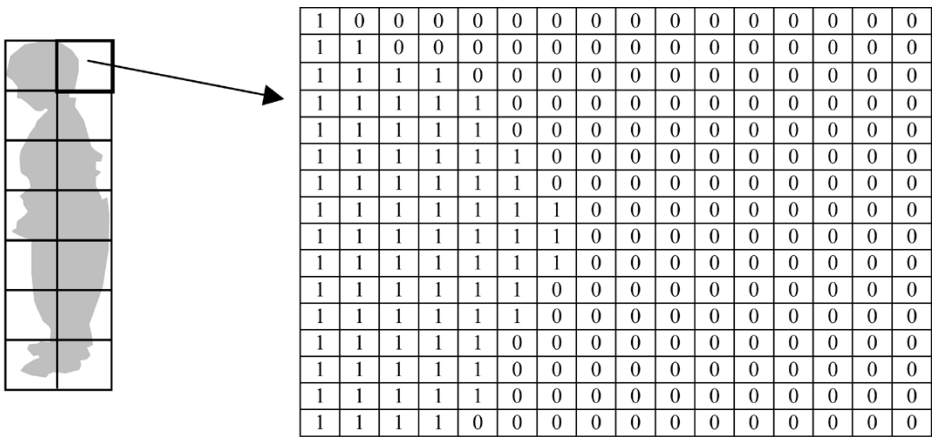

Fig. 1. Block-based shape representations (the pixels marked 0 are transparent pixel and those marked 1 are opaque pixels).

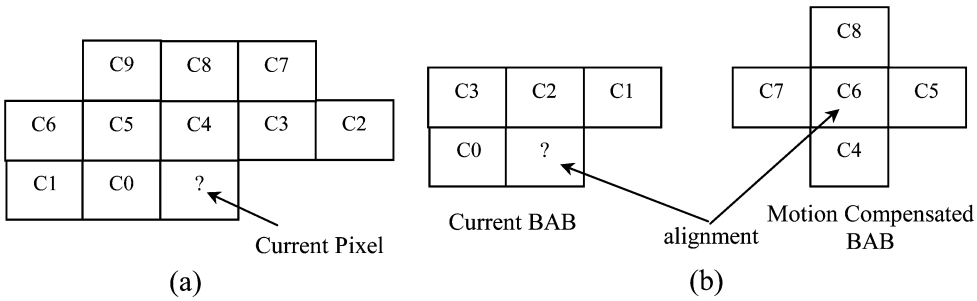

Fig. 2. Context for CAE encoding. (a) Intramode case. (b) Intermode case.

case, the bit budget is constant for each frame (for example, in some constant-bit-rate applications). Utilizing the bit budget constraint, the proposed algorithm provides the optimal coding parameters to assure the best visual quality of the reconstructed video frame.

The rest of the paper is organized as follows. In Section II, a brief overview of object-based video coding approaches is provided. In Section III, the problem formulation is presented. Section IV demonstrates the optimal solution. Section V provides the implementation details of our method on the MPEG-4 verification model and experimentally demonstrates its performance. We draw conclusions in the last section.

II. Overview of Object-Based Video Coding

Compared to conventional frame-based video coding, object-based video coding is based on the concept of encoding arbitrarily shaped VOs. The history of object-based video coding can be traced back to 1985, when a region-based image coding technique was first published [7], which was later extended to video encoding [8]. In 1989, an object-based analysis-synthesis coder (OBASC) was developed [9]. The image sequence is divided into arbitrarily shaped moving objects, which are encoded independently. The motivation behind this is that the shape of moving objects is more important than their texture, and that human observers are less sensitive to geometric distortions than coding artifacts of block-based coders. OBASC was mainly successful for simple video sequences.

Shape coding is a relatively new research topic (for a recent review see [10] and references therein). In this work, we only consider the context-based arithmetic encoding (CAE) method [11], which was adopted by the MPEG-4 standard. CAE is a bitmap-based method, which encodes for each pixel whether it belongs to the object or not; it is also a block-based method, where the binary shape information is coded utilizing the macroblock structure, by which binary alpha data are grouped within 16×16 binary alpha blocks (BAB) (see Fig. 1). Each BAB (if neither transparent nor opaque) is coded using CAE. A template of 10 pixels for ntermode (9 pixels for intermode) is used to define the context for predicting the alpha value of the current pixel. The templates for intra- and inter-BAB encoding are shown in Fig. 2. A probability table is predefined for the context of each pixel. After that, the sequence of pixels within the BAB drives an arithmetic encoder with a pair of alpha value and its associated probability. Due to the support of the models in Fig. 2, the encoding of a BAB depends on its neighbors to the left, above, above left, and above right.

BABs are classified into transparent, opaque, and border macroblocks using a test against the target BAB containing only zero-valued pixels and BAB containing only 255-valued pixels. In the classification, each BAB is subdivided into 16 elementary subblocks, each of size 4×4, and the BAB is classified as transparent or opaque only if all of these subblocks are of the same classification. The sum of absolute differences (SAD) between the subblock under test and the target subblock is compared to 16*Alpha_TH, where the Alpha_TH can take values from the set $\{0, 16, 32, 64, \ldots, 256\}$.To reduce the bit-rate, lossy representation of a border BAB might be adopted. According to it, the original BAB is successively downsampled by a conversion ratio factor (CR) of two or four, and then up-sampled back to the full-resolution. In intermode, there are seven BAB coding modes. The motion vector (MV) of a BAB is reconstructed by

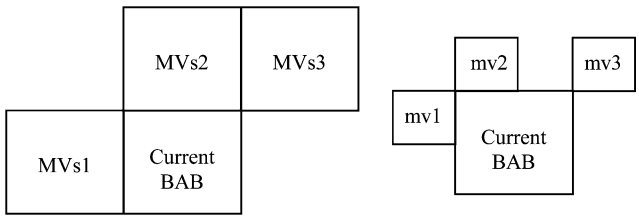

Fig. 3. Candidates for MVPs: MVs1, MVs2, MVs3 represent shape MVs for 16×16 macroblocks, while mv1, mv2, and mv3, are texture MVs for 8×8 blocks. The order for selecting MVPs is MVs1, MVs2, MVs3, mv1, mv2, and mv3.

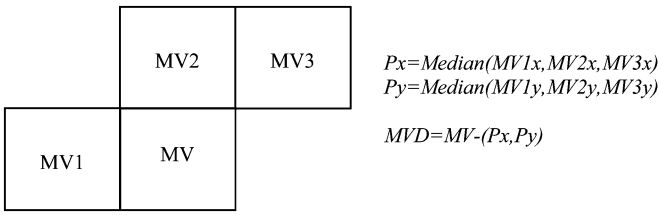

Fig. 4. Motion vector prediction.

predictive decoding it as $\mathrm{MV} = \mathrm{MVP} + \mathrm{MVD}$, where MVP is the MV predictor (see Fig. 3) and MVD (MV differences) lies in the range of $[-16, +16]$. Upon selection of MVP, the motion compensated (MC) error is computed by comparing the BAB predicted by MVP and the current BAB. If the computed MC error is smaller or equal to 16*Alpha_TH, for all 4×4 subblock, the MVP is directly utilized. Otherwise, MV is determined by searching around the MVP to find the location that minimizes the SAD of the 16×16 MC error.

Texture coding approaches in MPEG-4 are similar to most of the existing video coding standards. The VOPs are divided into 8×8 blocks followed by 2-D 8×8 discrete cosine transforms (DCT). The resulting DCT coefficients are quantized and the dc coefficients are also quantized (QDC) using a given step size. After quantization, the DCT coefficients in a block are zigzag scanned and a one-dimensional (1-D) string of coefficients is formed for entropy coding. In MPEG-4, the texture content of the macroblock's bitstream depends to a great extent on the reconstructed shape information. Before encoding, low-pass extrapolation (LPE) padding [12] (nonnormative tool) is applied to each 8×8 boundary (nontransparent and nonopaque) blocks. This involves taking the average of all luminance/chrominance values over all opaque pixels of the block, and all transparent pixels are given this average value. If the adaptive dc prediction is applied, the predicted dc selects either the QDC value of the immediately previous block or that of the block immediately above it. With the same prediction direction, either coefficients from the first row or the first column of a previously coded block are used to predict the coefficients of the current blocks. For predictive VOPs (P-VOPs), the texture data can be predictively coded, and a special padding technique called macroblock-based repetitive padding is applied on the reference VOP before motion estimation. After motion estimation, an MV and the corresponding motion-compensated residual are generated for each block. The MVs are coded differentially (see Fig. 4), while the residual data are coded as intracoded texture data, as mentioned above.

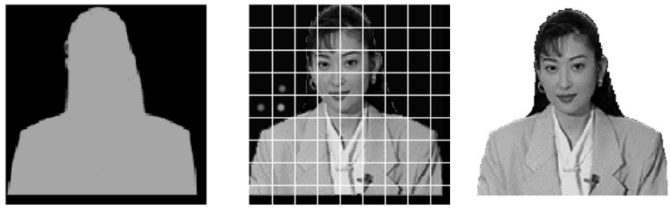

Fig. 5. Example of composition of shape and texture. (a) Shape. (b) Texture. (c) Composed object.

At the decoder side, the shape and texture data are composed to reconstruct the original video data. Since in this paper we assume that the shape information is represented by a binary alpha plane, after composition, only the corresponding texture within the shape boundary is kept (an example is shown in Fig. 5).

III. Problem Formulation

The problem at hand is to control both the shape and texture coding parameters to minimize the total (shape, texture, and motion) bit rate required to transmit a video sequences at some acceptable level of quality. These coding parameters for MPEG-4 will be explained in detail in Section V-A. We, therefore, formulate the following optimization problem

$$\text{Minimize } R, \quad \text{subject to } D \leq D_{\max} \tag{1}$$

where R is the total bit rate per frame, D is the resulting frame distortion, and $D_{\max}$ is the maximum allowable distortion. The same techniques, to be presented later, can be applied to solve the dual problem, that is

$$\text{Minimize } D, \quad \text{subject to } R \leq R_{\text{budget}} \tag{2}$$

where R_{budget} is the available bit budget per frame.

In object-based video, both overlapping and nonoverlapping VOPs are allowed. However, in both cases, VOs are encoded and transmitted separately. The user at the decoder side has the flexibility to determine the composition order of the objects; therefore, it is not practical to consider the joint encoding of various VOs unless there is a feedback-channel from the decoder providing to the encoder the information about the composition order of the VOs. In this paper, we do not assume the existence of such feedback-channel. Therefore, each VO forms a separate video sequence for processing, and hence the terms of frame and VOP are used interchangeably hereafter. That is, in this work, the optimal bit allocation among shape, motion, and texture is considered at the VOP level.

A. Rate

Let us denote by $\{m_1, m_2, \ldots, m_N\}$ the N raster-scan ordered macroblocks in the VOP, and by s_i the shape classification of each 8×8 block of a BAB associated with m_i. The set of coding parameters for a macroblock is referred to as the shape (or texture) decision vector. Let us denote by $V = \{V_1, V_2, \ldots, V_N\}$ the set of admissible shape decision vectors for the macroblocks, by v_i a shape decision vector for the ith macroblock ($v_i \in V_i$), and $v = \{v_1, v_2, \ldots, v_N\}$ the set of shape decision vectors for the VOP. Then, s_i is a function of

the shape decision vectors $v_{i-a},\ldots,v_i$, where a is the number of past macroblocks, macroblock m_i depends on. Typically, a is greater than 1, recalling that the encoding of a BAB depends on its neighbors to the left, above, above left, and above right. Similarly, let us denote by $W=\{W_1,W_2,\ldots,W_N\}$ the set of admissible texture decision vectors, w_i a texture decision vector for $m_i(w_i \in W_i)$, and $w=\{w_1,w_2,\ldots,w_N\}$ the set of texture decision vectors for the VOP. Let us denote by $R_{S_i}(v_{i-a},\ldots,v_i)$ the shape bit rate including the shape MV if present, and $R_{T_i}(s_i,w_{i-b},\ldots,w_i)$ the texture bit rate including the texture MV if present, for macroblock m_i, where b is the number of previous macroblocks the texture of m_i depends on. The reason that $R_{T_i}(s_i,w_{i-b},\ldots,w_i)$ depends on s_i is that the texture for transparent macroblocks inside the VOP is not coded. Clearly

$$R=R_{\text{syntax}}+\sum_{i=1}^{N}R_{S_i}(v_{i-a},\ldots,v_i)+\sum_{i=1}^{N}R_{T_i}(s_i,w_{i-b},\ldots,w_i) \quad (3)$$

where R_{syntax} represents the bits allocated to the data structure syntax of the VOP, and it is a fixed value if we assume each VOP frame is packed into a separate packet.

B. Distortion

In MPEG-4 shape and texture are measured separately [13]. The following expression is used to measure shape distortion

$$D_n=\frac{S_M}{S_o} \quad (4)$$

where S_M is the number of mismatched pixels in the reconstructed VOP and S_o the number of opaque pixels in the original VOP. This is also termed "relative area error."

The combined-channel peak signal-to-noise ratio (PSNR) is used to measure texture distortion. For an $l\times h$ pixel image in the 4:2:0 format, it is given in decibels (dB) by (5), shown at the bottom of the page, where $Y(x,y)$, $U(x,y)$, $V(x,y)$ are the original YUV intensity values of pixel (x,y), $Y'(x,y)$, $U'(x,y)$, $V'(x,y)$ are the corresponding reconstructed pixel intensity values, and the factor 1.5 is due to down sampling of the chrominance components by a factor of 2.

The metrics above are used separately and, therefore, they misrepresent the quality of the object-based encoded video. For example, a high PSNR when combined with a large D_n might provide a low quality video. A joint shape and texture distortion metric is, therefore, required. However, to the best of our knowledge, no such metric has been adopted and, therefore, it still remains an open problem.

The establishment of such a metric is not the focus of this paper, but instead the development of a framework for the optimal bit allocation in object-based video coding, given a joint shape and texture distortion metric. In order to proceed with the development of the algorithm and demonstrate its performance, we propose the following distortion metric

$$D=\alpha D_n+(1-\alpha)\beta D_T,\quad \alpha\in[0,1] \quad (6)$$

where D_n is defined in (4), α is a control parameter determined by the application, β is a scale parameter to ensure that the value of D_n and D_T are in the same range, and D_T is the texture distortion of the object expressed as (7), shown at the bottom of the page, where S_o^Y and S_o^{UV} denotes the set of opaque pixels in the Y and U,V planes, respectively, S_o the number of pixels in S_o^Y and S_o^{UV}. The distortion metric in (6) accounts for errors due to both shape and texture encoding, and it is based on the conventional distortion criteria for image/video quality evaluation. By adjusting the value of α, the user can determine the relative importance between shape and texture distortion. It is mentioned here that distortion metrics other than (6) can be used with the framework presented here. Clearly, the resulting optimal solution as well as the complexity of the optimization algorithm depends on the specific distortion method used.

Let us now denote by $D_i(s_i,w_{i-b},\ldots,w_i)$ the distortion for macroblock m_i defined as (8), shown at the bottom of the next page, where $d_{i,A}$ is the number of mismatched (alpha plane) pixels inside the macroblock, and $d_{i,Y}(x,y)$, $d_{i,U}(x,y)$, and $d_{i,V}(x,y)$ are the differences in intensity values for the Y, U and V components at pixel (x,y) of macroblock m_i. It is noted here that in obtaining the reconstructed intensity value for pixel (x,y) of m_i, w_{i-1}, $w_{i-2}\ldots$, and w_{i-b} were also used, due to the differential encoding of DCT coefficients and MVs. Due to (8) it is now clear that the distortion in (6) is equal to

$$D=\frac{\sum_{i=1}^{N}D_i(s_i,w_{i-b},\ldots,w_i)}{S_o}. \quad (9)$$

$$\text{PSNR}=10\log\left\{\frac{1.5\times l\times h\times 255^2}{\sum_{x=0}^{l-1}\sum_{y=0}^{h-1}(Y(x,y)-Y'(x,y))^2+\sum_{x=0}^{l/2-1}\sum_{y=0}^{h/2-1}[(U(x,y)-U'(x,y))^2+(V(x,y)-V'(x,y))^2]}\right\} \quad (5)$$

$$D_T=\frac{\sum\sum_{(x,y)\in S_o^Y}(Y(x,y)-Y'(x,y))^2+\sum\sum_{(x,y)\in S_o^{UV}}[(U(x,y)-U'(x,y))^2+(V(x,y)-V'(x,y))^2]}{1.5S_o} \quad (7)$$

IV. Optimal Solution

In this section, we provide an optimal solution for problem (1), which can be rewritten as

$$\begin{aligned}\text{Minimize}\quad & \sum_{i=1}^{N} R_{S_i}(v_{i-a},\ldots,v_i) \\ & +\sum_{i=1}^{N} R_{T_i}(s_i,w_{i-b},\ldots,w_i) \\ \text{such that}\quad & \sum_{i=1}^{N} D_i(s_i,w_{i-b},\ldots,w_i)\le S_o D_{\max} \end{aligned} \tag{10}$$

where the minimization is performed with respect to the variables s_i, $v_{i-a},\ldots,v_i$, and $w_{i-b},\ldots,w_i$.

We now define the set of admissible decision vectors $U = V \times W$. For each macroblock m_i there is a decision vector $u_i = (v_i, w_i)$ and (10) can be simplified as

$$\begin{aligned}\underset{u}{\text{Minimize}}\quad & \sum_{i=1}^{N}[R_i(u_{i-a},\ldots,u_i)] \\ \text{such that}\quad & \sum_{i=1}^{N} D_i(u_{i-a},\ldots,u_i)\le S_o D_{\max} \end{aligned} \tag{11}$$

where $R_i(u_{i-a},\ldots,u_i) = R_{S_i}(v_{i-a},\ldots,v_i) + R_{T_i}(s_i,w_{i-b},\ldots,w_i)$, $D_i(u_{i-a},\ldots,u_i) = D_i(s_i,w_{i-b},\ldots,w_i)$, and $u = [u_1,u_2,\ldots,u_N]^T$ (without loss of generality, we assume that $a \ge b$).

We derive a solution to problem (11) using the Lagrange multiplier method to relax the constraint, so that the relaxed problem can be solved using a shortest path algorithm. We first define the Lagrangian cost function

$$J_\lambda(u) = \sum_{i=1}^{N}[R_i(u_{i-a},\ldots,u_i) + \lambda D_i(u_{i-a},\ldots,u_i)] \tag{12}$$

where λ is the Lagrange multiplier. It has been shown in [14] and [15] that if there is a λ^* such that $u^* = \arg[\min_u J_{\lambda^*}(u)]$, and which leads to $\sum_{i=1}^{N} D_i(u_{i-a},\ldots,u_i) = S_o D_{\max}$, then u^* is also an optimal solution to (11). It is well known that when λ sweeps from zero to infinity, the solution to (12) traces the convex hull of the operational rate distortion function, which is a nonincreasing function. Hence, bisection or the fast convex search presented in [16] can be used to find λ^*. Therefore, if we can find the optimal solution to the unconstrained problem

$$\underset{u}{\text{Minimize}} \sum_{i=1}^{N}[R_i(u_{i-a},\ldots,u_i) + \lambda D_i(u_{i-a},\ldots,u_i)] \tag{13}$$

we can find the optimal λ^*, and the convex hull approximation to the constrained problem (11).

To implement the algorithm for solving the optimization problem (13), we create a cost function $C_k(u_{k-a},\ldots,u_k)$, which represents the minimum total rate and distortion up to and including macroblock m_k, given that $u_{k-a},\ldots,u_k$ are the decision vectors for macroblocks $m_{k-a},\ldots,m_k$. Clearly

$$J_\lambda(u) = \min_{u_{N-a},\ldots,u_N} C_N(u_{N-a},\ldots,u_N). \tag{14}$$

The key observation for deriving an efficient algorithm is the fact that given $a+1$ decision vectors $u_{k-a-1},\ldots,u_{k-1}$ for macroblocks $m_{k-a-1},\ldots,m_{k-1}$, and the cost function $C_{k-1}(u_{k-a-1},\ldots,u_{k-1})$, the selection of the next decision vector u_k is independent of the selection of the previous decision vectors $u_1,u_2,\ldots,u_{k-a-2}$. This is true since the cost function can be expressed recursively as

$$\begin{aligned} C_k(u_{k-a},\ldots,u_k) = \min_{u_{k-a-1},\ldots,u_{k-1}} & [C_{k-1}(u_{k-a-1},\ldots,u_{k-1}) \\ & +R_k(u_{k-a},\ldots,u_k) + \lambda D_k(u_{k-a},\ldots,u_k)]. \end{aligned} \tag{15}$$

The recursive representation of the cost function above makes the future step of the optimization process independent from its past step, which is the foundation of dynamic programming. It is mentioned here that the presented algorithm can also be used to solve the dual problem (2).

The problem can be converted into a graph theoretic problem of finding the shortest path in a directed acyclic graph (DAG) [17]. The computational complexity of the algorithm is $O(N \times |U|^{\max(a,b)+1})$, with $|U|$ denoting the cardinality of U, which depends directly on the value of a and b, but is still much more efficient than the exponential computational complexity of an exhaustive search algorithm. In [18], a similar DP algorithm is applied to solve the bit allocation problem between displacement vector field and displaced frame difference in motion-compensated video coding.

The proposed optimal scheme is also applicable to grayscale alpha plane cases, where the gray-level alpha plane is encoded as its support function and the alpha values on the support, where the support function is encoded by binary shape coding and the alpha values are encoded as texture data. Clearly, (6) has to be modified to consider the new factor brought in.

V. Experimental Results

The problem formulation and solution approach presented in this paper are general and applicable to any texture encoding method and block-based shape coding methods. In our experiment, we implemented the proposed optimal bit allocation scheme utilizing the MPEG-4 verification model [1], [13], [19],

$$D_i(s_i,w_{i-b},\ldots,w_i) = \frac{\alpha d_{i,A} + (1-\alpha)\beta\left\{\sum\sum_{(x,y)\in S_o^{i,Y}} d_{i,Y}(x,y)^2 + \sum\sum_{(x,y)\in S_o^{i,UV}}\left[d_{i,U}(x,y)^2 + d_{i,V}(x,y)^2\right]\right\}}{1.5} \tag{8}$$

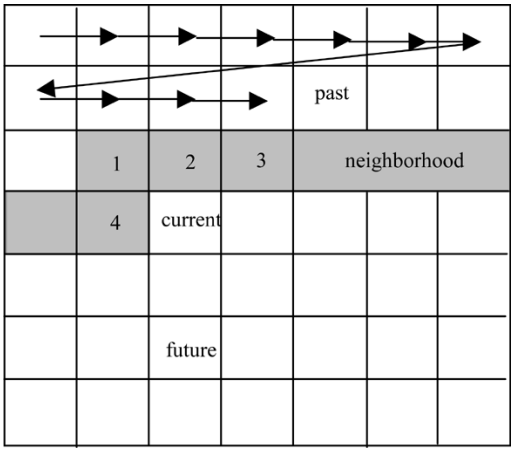

Fig. 6. The neighborhood of the current macroblock.

and, thus, selecting the conventional 2-D DCT method for texture encoding. We report the simulation details in Section V-A and the experimental results in Section V-B.

A. System Simulations

In the MPEG-4 verification model for all macroblocks of a VOP, the same value of Alpha_TH is used to control the shape approximation level and the shape MV. In addition, the values of shape parameters, such as BAB type and CR, are transmitted to the decoder, while the value of Alpha_TH is not. This means that the parameter Alpha_TH only indirectly affects the rate-distortion characteristic of the video codec, and it is, therefore, not directly accounted for in the optimization.

The encoding schemes of shape and texture make the macroblocks highly dependent on their neighbors. In shape coding, the border macroblocks at the VO level need to be further processed by CAE, which makes the encoding of a BAB depend on its neighbors to the left, above, above-left, and above right. The processes of adaptive dc/ac prediction and the MVP and encoding involve the current macroblock and its neighbors. As shown in Fig. 6, the encoding of the current macroblock will only depend on the encoding of macroblocks 1, 2, 3, and 4. In other words, after the decision vectors for macroblocks 1, 2, 3, 4, and the current macroblock are decided, the rate for the current macroblock is fixed for both intermode and intramode encoding.

As is the case with all video compression standards, only the structure of the decoder is specified by the standard. Our optimization work addresses the optimal selection of the coding parameters so that the video is coded to meet certain constraints in quality or bit rate. From the MPEG-4 VOP data structure, the adjustable parameters for intra-mode include BAB type, CR, ST, and quantization step size. For inter-mode coding, the additional parameters MVDs and MVD need to be taken into account (see Table I for definition of these coding parameters). In MPEG-4, it is possible to modify the quantizer value at the macroblock level, although only a small adjustment (-1 or -2 or $+1$ or $+2$) in the value of the most recent quantizer is permitted.

We assume that the N macroblocks $m_1, m_2, \ldots, m_N$ of the current VOP are arranged into K columns, and they are numbered following the horizontal scan order. If the block in Fig. 6 represents a VOP, then $N = 49$ and $K = 7$. Therefore, a in (11) is equal to $K + 1$. Every macroblock has a BAB type $b_i \in B_i$, an MVDs ($ms_i \in MS_i$), a CR ($c_i \in C_i$), an ST ($s_i \in S_i$), a quantizer step size $q_i \in Q_i$, and an MVD ($mv_i \in MV_i$) associated with it, where B_i is the set of all admissible BAB type for m_i, MS_i is the set of all admissible shape MVs for m_i, C_i is the set of all admissible CR for m_i, S_i is the set of all admissible ST for m_i, Q_i is the set of all admissible quantizer step sizes for m_i, and MV_i is the set of all admissible texture MV for m_i. Let us define a decision vector $u_i = [b_i, ms_i, c_i, s_i, q_i, mv_i,] \in U_i$ for every macroblock m_i, with $U_i = B_i \times MS_i \times C_i \times S_i \times Q_i \times MV_i$ the admissible decision vector set for m_i.

TABLE I
DEFINITION OF MPEG-4 CODING PARAMETERS

BAB type	BAB coding modes (for example, transparent or opaque)
CR	Conversion Ratio (subsampling ratio for CAE coding)
ST	Scan Type (predefined scan order of BAB pixels)
MVDs	Motion vector data for shape
MVD	Motion vector data for texture
QP	Texture quantization step size

B. Experimental Results

A number of experiments have been conducted with the QCIF sequences "Akiyo," "Bream," "Children," and "Cyclamen," and for various choices for the value of α, some of which are reported here. We implemented our codec using the proposed bit allocation scheme and the basic coding algorithms specified in MPEG-4 video verification model. In our experiments, we set $\beta = 1/255$ in (6), so that the two quantities D_n and D_T are in comparable range. We demonstrate the optimal bit allocation results and discuss their dependency on the value of α in the first 2 sets of experiments. Then, we use MoMuSys, a software implementation of MPEG-4 Video Verification Model, as a reference to compare the MPEG-4 results with the ones obtained with the proposed algorithm. It is important to point out that we are using the same algorithm with MoMuSys as demonstrated by the third set of experiments.

In the first set of experiments, we encode the first "Children" frame with various α values ($\alpha = 0.2$, $\alpha = 0.5$, and $\alpha = 0.8$) and various bit budgets (4000, 8000, and 12 000). Fig. 7 shows the results and Table II shows the detailed rate and distortion for each case. In Table II, the values of D in (6), D_n in (4), along with $D_{T,\mathrm{PSNR}}$ defined by $D_{\mathrm{dB}} = -10\log_{10}\left(D_T/255^2\right)$. The last measure is shown since it represents the standard way for measuring texture distortion. From this figure and table, it is easy to verify that for $\alpha = 0.8$, since shape is given higher weight than texture it has been well reserved for all bit rates, while this is not the case for lower values of α and low bit rates.

In the second set of experiments, we explore the scheme of optimal bit allocation between shape and texture by encoding the first 30 frames of the "Bream" sequence in both intra- and intermode. In Fig. 8(a), the rate-distortion curves (with $\alpha = 0.5$) obtained by the proposed optimal approach are shown. The vertical axis represents the average distortion D_{dB} over 30 frames, where $D_{\mathrm{dB}} = -10\log_{10} D$. The corresponding average shape and texture bit rates are shown in Fig. 8(b) [Please notice that there is an one-to-one correspondence between the operating

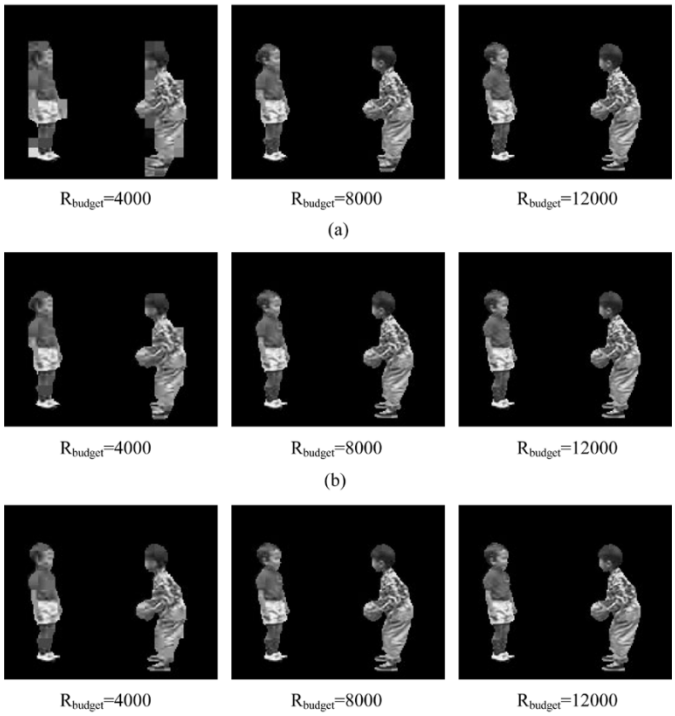

Fig. 7. Reconstructed frame 0 of "Children" sequence for various values of α and bit budget. (a) $\alpha = 0.2$. (b) $\alpha = 0.5$. (c) $\alpha = 0.8$.

TABLE II
EXPERIMENTAL DATA FOR FIRST "CHILDREN" FRAME. (A) $\alpha = 0.2$. (B) $\alpha = 0.5$. (C) $\alpha = 0.8$

Rate Budget	Shape bits	D	D_n	$D_{T,PSNR}$ (dB)
4000	*362*	*0.968*	*0.323*	*23.54*
8000	*503*	*0.352*	*0.093*	*27.87*
12000	*790*	*0.176*	*0.024*	*30.76*

(a)

Rate Budget	Shape bits	D	D_n	$D_{T,PSNR}$(dB)
4000	*493*	*0.652*	*0.102*	*23.27*
8000	*858*	*0.236*	*0.016*	*27.47*
12000	*1002*	*0.115*	*0.002*	*30.50*

(b)

Rate Budget	Shape bits	D	D_n	$D_{T,PSNR}$ (dB)
4000	*768*	*0.280*	*0.030*	*22.99*
8000	*1014*	*0.096*	*0.001*	*27.30*
12000	*1028*	*0.046*	*0*	*30.44*

(c)

points in Fig. 8(a) and (b)]. It is clear from Fig. 8(a) that intermode encoding saves a considerable number of bits compared to intramode encoding, and from Fig. 8(b) that shape information only represents a small portion (in most cases, less than 20%) of the overall bit budget. It is interesting to observe that the texture versus shape bit rate tradeoff is similar for both intra- and

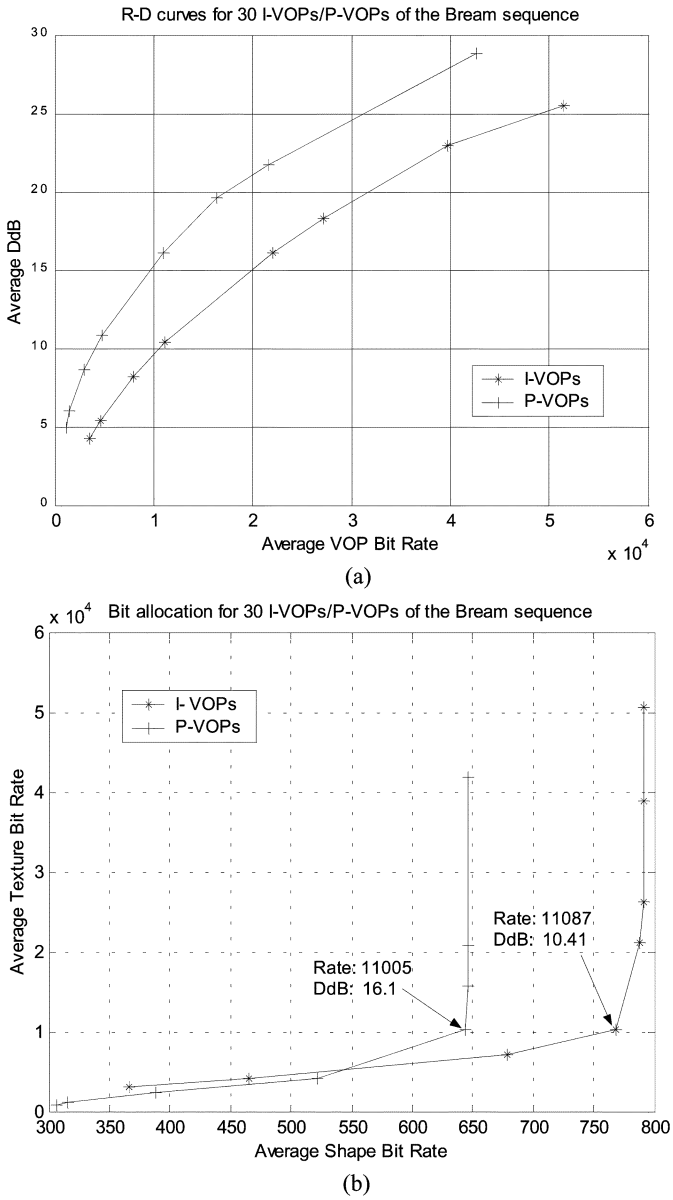

Fig. 8. Experimental results for "Bream" sequence ($\alpha = 0.5$). (a) VOP PSNR versus VOP bit rate. (b) Shape bit rate versus texture bit rate.

inter-encoding, and there is a salient turning point in each curve. Let us take a closer look at Fig. 8(b); for intramode encoding, when the PSNR is between 4 and 10.4 dB, the shape bits increase from 360 to around 770, and texture bits increase from 3000 to around 10 000; after that, the texture bits go up steeply from 10 000 to 50 000 and shape bits only change slightly. Similarly, for intermode encoding, when the PSNR is between 5 dB and 16 dB, the shape bits increase from 300 to around 650, and the texture bits increase from 3000 to 10 000. However, when the PSNR keeps increasing to 28.5 dB, the texture bits go up steeply from 10 000 to 40 000 and shape bits only show a slight change. It is very important to notice that the shape bit rate for the "turning point" of the curve is equal to or almost equal to the rate for lossless shape, which means that the proposed optimal approach ends up coding the shape losslessly when the VOP bit budget is high enough. The loss of shape information in this case will cause higher distortion to the reconstructed video than the same loss (in bits) of texture data.

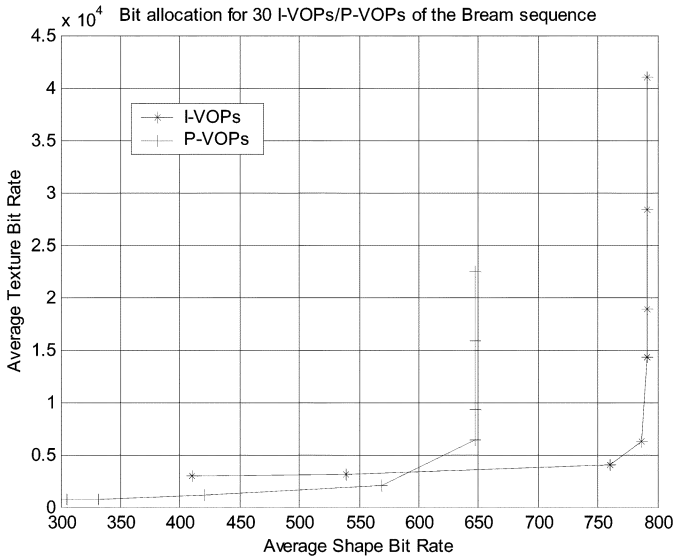

Fig. 9. Experimental results for "Bream" sequence ($\alpha = 0.8$).

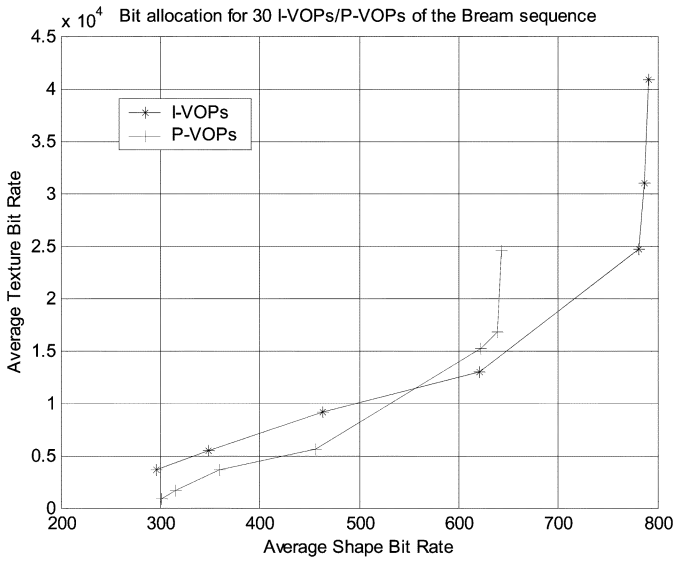

Fig. 10. Experimental results for "Bream" sequence ($\alpha = 0.2$).

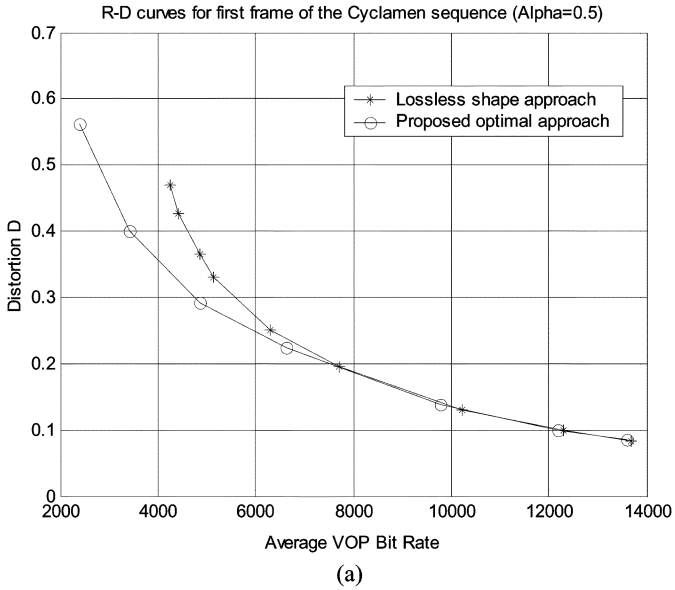

Fig. 11. Rate-distortion curve for encoding "Cyclamen" sequence ($\alpha = 0.5$).

The same experiments was conducted with $\alpha = 0.2$ and $\alpha = 0.8$. For $\alpha = 0.8$, the curve in Fig. 9 accepts the following interpretation: for low bit rates, the bits are first allocated to maintain the lowest quality of texture (e.g., $\mathrm{QP} = 31$), and the rest of the bits are assigned to shape; as the bit rate increases, the shape is losslessly coded, and the rest of the bits are assigned to code the texture. For $\alpha = 0.2$ (Fig. 10), the shape clearly is assigned a smaller weight than texture and, therefore, the shape is not losslessly encoded until the overall bit rate is considerably increased.

What the experimental results above demonstrate is that in all cases there is a "turning point" in the "average texture bit rate versus average shape bit rate" plots, below which the shape is encoded in a lossy fashion and above which the shape is encoded in a lossless fashion. That is, after the turning point the proposed algorithm converts to a lossless shape algorithm followed by an operational rate-distortion (RD) optimal texture algorithm (henceforth referred to as *lossless shape algorithm*).

An important question that arises then is what the location of this turning point depends on? It depends on the complexity of the shape or on the ratio of texture over shape bits, or the percentage of the texture and shape bits with respect to the total bit rate. If this ratio is close to one (i.e., shape and texture bits are about 50%-50%) then there are more bits that if taken away from the shape (resulting in lossy shape) might make a difference in improving the quality of the texture. If, however, this ratio is very large (for example, 20, i.e., the lossless shape is only about 5% of the total bit rate) then this turning point occurs at low bit rates. Now this ratio is also a function of α; that is when α increases the ratio decreases, which comes from the fact that texture is decided (through α) to be "less important" than shape and, therefore, fewer bits are allocated to it (while clearly the bits for lossless shape are constant). For some applications, the choosing of an appropriate value for α could be a nontrivial task.

Clearly one of the benefits of the proposed algorithm is that the determination of this turning point is done automatically, that is, one does not have to predict or guess or estimate through

(a) (b) (c)

Fig. 12. Rate-distortion curve for encoding "Cyclamen" sequence ($\alpha = 0.5$). (a) Lossless shape approach $D = 0.365$, $D_{T,PSNR} = 25.43$ dB. (b) Proposed approach $D = 0.292$, $D_{T,PSNR} = 27.13$ dB. (c) Original frame.

any other means (i.e., analysis of the shape complexity) its position. The benefit of the proposed algorithm over the lossless shape algorithm increases the higher (in terms of shape bits) this turning point is (that is, there are more operating points for which lossy shape is the optimal solution). In demonstrating through an example the potential benefit of the proposed algorithm over the lossless shape algorithm for rates below the turning point we present the following experiment.

In Fig. 11, we encode the "Cyclamen" sequence and show the rate-distortion curve by both approaches, where we use distortion D in Fig. 11(a) and texture only distortion D_T in decibels in Fig. 11(b). The gain is up to 2 dB, although the benefits decrease when the bit rate increases as expected. In Fig. 12(c), we show the resulted first frame when the bit budget is 4850 bits, where the lossless shape approach [as shown in Fig. 12(a)] spends 2516 bits for shape while the proposed approach [as shown in Fig. 12(b)] only spends 1045 bits for shape. The savings of 1471 shape bits by the proposed approach improved the texture quality by about 1.7 dB. In addition, we find that the compressed bit rate range of the proposed approach can be extended to a much lower bit rate compared to the lossless shape approach, which might be of importance in very low bit rate applications.

In the last set of experiments, we first encode the first "Bream" frame as an I-VOP, and compare the result from our proposed optimal approach with that of MoMuSys, by exhaustively trying all combinations of parameters (Alpha_TH and QP) which result in all possible operating points, as shown in Fig. 13(a). As expected, our result in addition to providing solutions on the convex hull of all operating points, also demonstrates a small gain in RD quality, due to the selection of adjustable parameters different than Alpha_TH or QP. As mentioned before, Alpha_TH only indirectly affects the rate-distortion characteristic of the video encoding, so that the operating points generated by exhaustively trying all possible Alpha_TH values may not cover all possible combinations of the coding parameters (like CR and ST) which explains the small RD gains. Our experimental results on other sequences also show the same tendency. In addition, we encode the first "Bream" frame losslessly and use it as a reference to encode the second frame as a P-VOP. We again compare our result with MoMuSys by exhaustively trying all combinations of coding parameters, as shown in Fig. 13(b). The same conclusions are drawn for this experiment. Clearly the benefit of the proposed algorithm is that it is guaranteed to achieve the operational rate distortion optimal performance in an efficient way, that is, without requiring an exhaustive search or relying on the available rate controller.

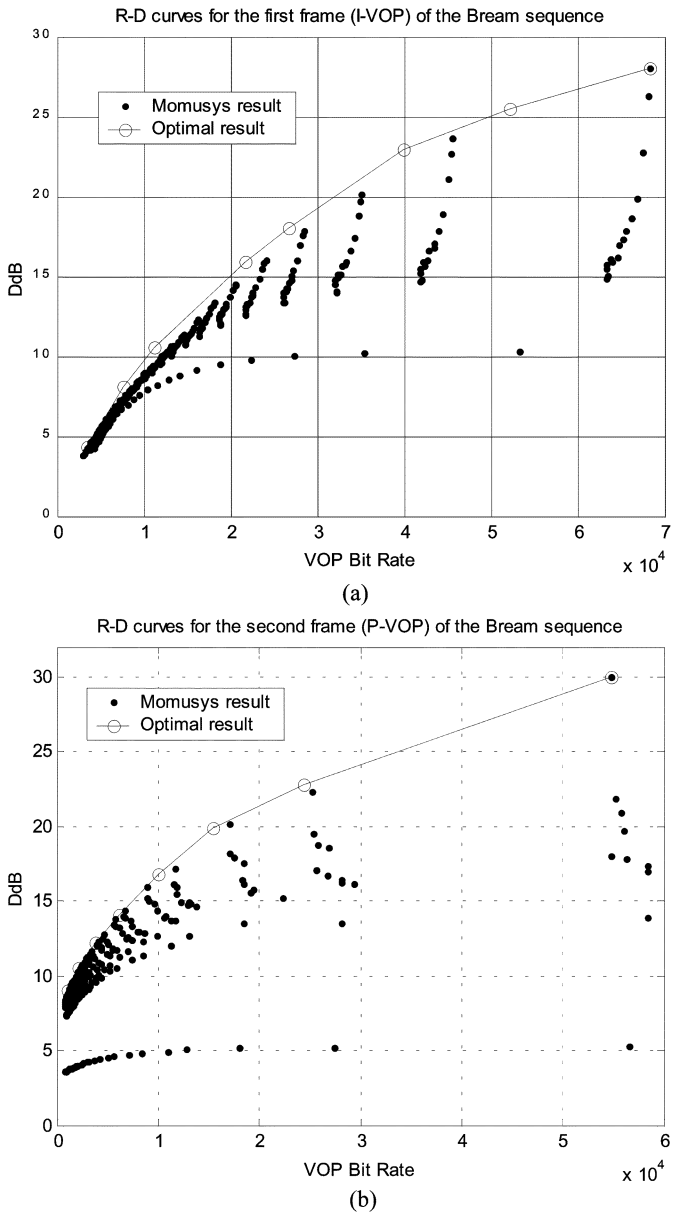

Fig. 13. Compare our proposed optimal approach with MoMuSys. (a) Intramode testing results. (b) intermode testing results.

VI. Conclusion

In this paper, we presented an operational rate-distortion optimal bit allocation scheme among shape, motion, and texture for the encoding of object-based video. The solution of the optimization problem is obtained by applying the Lagrange multiplier method and dynamic programming. We addressed the question of under how much is the gain of lossy shape encoding (the outcome of the optimal algorithm) over a lossless shape algorithm. We also described the factors that affect this gain and considered experimental results. There may indeed be cases when the shape bits are only a small fraction of the total bits and hence lossy shape is only an optimal solution for very low bit rates for which the quality may not be acceptable. On the other hand there are scenes for which lossy shape encoding provides a benefit over losseless shape.

Finally, the proposed optimal joint shape and texture encoding scheme is specific to codecs with block-based shape coding approaches. Different mechanisms will be needed for codes employing other shape coding methods.

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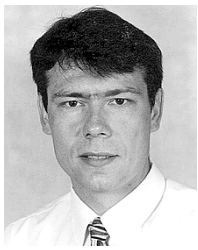

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