Multiterminal Video Coding

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Abstract—Following recent works on the rate region of the quadratic Gaussian two-terminal source coding problem and limit-approaching code designs, this paper examines multiterminal source coding of two correlated video sequences to save the sum rate over independent coding. Specifically, the first video sequence is coded by H.264 and used at the joint decoder to facilitate Wyner-Ziv coding of the second video sequence. The first I-frame of the right sequence is successively coded by H.264 and Slepian-Wolf coding. An efficient stereo matching algorithm based on loopy belief propagation is then adopted at the decoder to produce pixel-level disparity maps between the corresponding frames of the two decoded video sequences on the fly. Based on the disparity maps, side information for both motion vectors and motion-compensated residual frames of the second sequence are generated at the decoder before Wyner-Ziv encoding. Experimental results on stereo video sequences using H.264, LDPC codes for Slepian-Wolf coding of the motion vectors and scalar quantization in conjunction with LDPC codes for Wyner-Ziv coding of the residual coefficients show savings in terms of the sum-rate when compared to separate H.264 coding at the same video quality.

Index terms: multiterminal video coding, stereo matching, H.264 standard.

I. INTRODUCTION

Multiterminal (MT) source coding [1] is gaining research interest lately due to its potential applications in distributed sensor networks and distributed multiview video coding. Theoretical limit of MT source coding of jointly Gaussian sources was given recently in [2] for the direct setting (with two encoders) where the encoders directly observe the sources, and in [3] for the indirect/CEO setting where the encoders observe independently corrupted versions of the same source. Practical MT code designs based on generalized coset codes were provided by Pradhan and Ramchandran in [4]. In earlier works, we proposed a framework for practical MT source coding based on Slepian-Wolf coded quantization [5], which employs the approach of vector quantization followed by Slepian-Wolf coding (SWC) [6]. However, the code designs in [4], [5] are for ideal Gaussian sources assuming a priori known correlation. When dealing with practical (e.g., video) sources, correlation modeling is one of the key issues in efficient MT video coding. In this paper, we focus on MT video code design for two correlated video sequences captured by calibrated cameras.

In general, effective coding of a single/monocular video sequence necessitates exploitation of both spatial and temporal redundancies within the sequence. H.264 [7] provides the currently most efficient solution by using motion estimation/compensation to strip off the temporal redundancy between frames, the DCT of the resulting motion-compensated residual frames for energy compaction and decorrelation, and variable-length coding for compression.

For stereo video sequences synchronously captured by two calibrated video cameras, the compression efficiency can be further improved by exploiting the inter-sequence correlation (as done in the MPEG-2 stereo video coding standard [8]) in a joint encoding setup.

For MT video coding, although the encoders cannot communicate with each other, the 3D geometric information of the cameras can still help to exploit the binocular correlation between the stereo pair. Many works [9], [10], [11], [12], [13] are done for multiview video coding using this idea. Recently, Song et al. [14] designed a model-based coding scheme that combines 3D geometry with distributed coding. A further attempt to obtain pixel-level stereo correspondence leads to stereo matching, which is a fundamental problem in stereo vision, and has been extensively studied in the past by many researchers (see [15] and references therein). Assuming knowledge of the camera configurations, stereo matching computes a disparity map from a stereo image pair. It can be formulated as an optimization problem that minimizes the image dissimilarity energy. Quantitative evaluations of different stereo matching algorithms in terms of bad pixel percentage (available at http://cat.middlebury.edu/stereo) showed that the BP based algorithm [15] is among the most efficient.

We describe in this paper an MT video codec that is capable of outperforming separate H.264 coding of two stereo video sequences. Our codec shares the basic structure of Slepian-Wolf coded quantization [5] for direct MT source coding of two Gaussian sources. Specifically, the left video sequence is compressed by the left encoder using H.264 and a reconstructed version is available at the joint decoder. Then, the first I-frame of the right sequence is successively coded: a low-quality version is generated by H.264 and sent to the decoder to obtain a rough disparity map, which is used to compress the refinement bit stream of the right I-frame using SWC with the decoded left I-frame as side information. This way, the low-quality version is thus refined, as well as the disparity map between the I-frames. Using the disparity map as a initial point-to-point correspondence for the remaining P-frames of the right sequence, the joint decoder generates side informations for both the motion vectors and the motion-compensated residual frame by imposing an "identical motion constraint" (which means the corresponding points in the left and right scenes must have identical 3D motions). With side information available at the decoder, we implement SWC of the motion vectors via low-density parity-check (LDPC) coding, and Wyner-Ziv coding (WZC) [17] of the motion-compensated residual frames via Slepian-Wolf coded scalar quantization.
H.264 bitstream consists of header bits, motion vector bits, and texture bits. In the low-rate regime, most of the rate budget is spent on the header; and there is not much room for further savings in the texture bits from WZC in this scenario. In the high-rate regime, additional WZC of the motion-compensated residual frames is a must, but it is more challenging because the bad matching pixels in the disparity map and motion field will introduce much more noise to the side information of residual frame pixels than to that of the motion vectors (which are generated at macroblock level instead of pixel level). This paper presents results SWC of the motion vector bits at low rate, and on WZC of the I-frame and the residual P-frames at high rate. These results indicate savings in terms of the sum-rate when compared to separate H.264 coding at the same video quality.

II. MT VIDEO CODING

Our proposed MT video coding scheme is depicted in Fig. 1 (right I-frame) and Fig. 2 (right P-frame). Let \( \mathcal{L} = \{L_1, L_2, ..., L_n\} \) and \( \mathcal{R} = \{R_1, R_2, ..., R_n\} \) be the left and right stereo video sequences, respectively. First, the left sequence \( \mathcal{L} \) is compressed at Encoder 1 by H.264 and transmitted to the joint decoder, using a transmission rate of \( R_L \) bits per second (bps). Assume that only the first frame \( L_1 \) is intra-coded I-frame and all the other frames \( L_2, ..., L_n \) are inter-coded P-frames. Then the first frame \( R_1 \) of right sequence is intra-coded using a large quantization parameter (QP) to produce a low-quality reconstruction \( \hat{R}_1 \) at the decoder. A rough disparity map \( D_1 \) between \( R_1 \) and the decoded left I-frame \( L_1^D \) is generated, and is used to produce a side information \( R_{l1}^D \) by warping \( L_1^D \). Now the encoder re-quantizes the residual I-frame using a small QP, and the refining lower bitplanes are compressed by SWC with the syndromes sent to the decoder. Using both the side information \( R_{l1}^D \) and the decoded higher bitplanes (from H.264), the refinement bitplanes are decoded and hence the final decoded I-frame \( R_1^D \) and disparity \( D_0 \) are generated. Denote \( R_{l1}^D \) as the bit rate (in bps) that Encoder 2 spent on coding \( R_1 \). The coded bitstream for the \( k \)-th inter-coded frame \( R_k \) \( (k = 2, 3, ..., n) \) consists of three parts, namely, the overhead bits \( O_k^R \), the motion vector bits \( M_k^R \), and texture bits \( C_k^R \) for the DCT coefficients. We denote the reconstructed version of the left and right sequences as \( \mathcal{L}^D = \{L_1^D, ..., L_n^D\} \) and \( \mathcal{R}^D = \{R_1^D, ..., R_n^D\} \), respectively.

Before compressing \( R_k \) for \( k = 2, ..., n \) at Encoder 2, we assume that the joint decoder has access to the reconstructions \( \{L_1^D, ..., L_{k-1}^D, L_k^D\} \) and \( \{R_1^D, ..., R_{k-1}^D\} \). We first employ stereo matching to generate disparity map \( D_{k-1} \) between \( L_{k-1}^D \) and \( R_{k-1}^D \). Using a slightly modified stereo matching algorithm (by allowing vertical disparities), we also obtain a forward motion field \( M_k^L \) from \( L_{k-1}^D \) to \( L_k^D \). Then, assume that the 3D stereo camera settings are known, and follow the “identical motion constraint” we apply a novel motion fusing algorithm to produce the right forward motion field \( M_k^R \) based on the known information \( D_{k-1} \) and \( M_k^L \). Clearly, the motion vectors \( M_k^R \) in the H.264 bitstream are correlated to the motion field \( M_k^R \). Hence SWC can be employed to code \( M_k^R \) with \( M_k^R \) as decoder side information.

Next, \( R_{k-1}^D \) is warped according to the right motion field \( M_k^R \) generating an estimate \( \hat{R}_k^w \) of the \( k \)-th frame \( R_k \). Now the \( k \)-th disparity map \( D_k \) can be obtained from \( L_k^D \) and \( R_{k-1}^D \). Assume ideal Slepian-Wolf decoding, such that \( M_k^R \) is perfectly reconstructed at the decoder, then exactly the same motion compensated frame \( R_k^M \) at the encoder can be formed by warping \( R_{k-1}^D \) according to \( M_k^R \). Consequently, the source and the side information for WZC can be computed as

\[
X_k = R_k - \text{warp}(R_{k-1}^D, M_k^R) = R_k - R_k^M; \\
Y_k = \text{warp}(L_k^D, D_k) - \text{warp}(R_{k-1}^D, M_k^R),
\]

respectively. Finally, WZC is employed to explore the remaining correlation between \( X_k \) and \( Y_k \) and joint decoder re-constructs \( \mathcal{R} = \{R_1^D, R_2^D, ..., R_n^D\} \) using a total transmission rate of \( R_Y = \sum_{i=1}^n R_Y^i \) bps.

III. I-Frame Compression

The right I-frame is first intra-coded with \( QP = P_1 \). The resulting H.264 bitstream is directly sent to the decoder, and a rough disparity map \( D_1 \) is generated by matching the reconstructed right I-frame \( R_1^w \) (\( QP = P_1 \)) with \( L_1^D \) (\( QP = P_b = P_1 - 6k \)). Denote the intra-predicted right I-frame as \( R_1^i \) (\( QP = P_0 \)). Then the residual frame \( R_1 - R_1^w \) is transformed and re-quantized with \( QP = P_h \). Since quantization step size doubles for every increment of 6 in \( QP \), all but the lower \( k \) bitplanes of the re-quantized coefficients are already transmitted by H.264. The rest \( k \) refinement bitplanes are compressed by Slepian-Wolf Encoding using multilevel Slepian-Wolf decoding [5] with side information \( R_1^r = \text{warp}(L_1^D, D_1) \) and the decoded higher bitplanes.

IV. Motion Field Estimation and Motion Fusion

Although originally designed for stereo matching, the BP based algorithm [15], [16] can also be applied for motion field estimation. Since most stereo cameras are aligned such that no vertical disparity exists between corresponding pixels, the algorithm in [15] only allows horizontal disparities, which are clearly not enough for motion field. Hence we slightly modify the above algorithm by allowing vertical disparities: all scalar disparities \( d_v \) become vector disparities \( d \); the Birchfield and Tomasi’s pixel dissimilarity \( |F(s,d_v,I)| \) [15] is changed to

\[
F(s,d_v,I) = \min\{\tilde{d}(s,s',I)/\sigma_f, \tilde{d}(s',s,I)/\sigma_f\},
\]

where \( \tilde{d}(s,s',I) \) and \( \tilde{d}(s',s,I) \) are pixel dissimilarities at pixel positions \( s \) and \( s' \), respectively, and \( \sigma_f \) is the noise variance in the image.
where \( d(s, s', I) = \min \{|I_L(s) - I_R(s')|, |I_L(s) - I_R(s')|, |I_L(s) - I_R(s')|, |I_L(s) - I_R(s')|\} \), 
\( s' \) is the matching pixel of \( s \) with disparity \( d_s \), and 
\( \{I_R(s'), I_R(s'), I_R(s'), I_R(s')\} \) are the linearly interpolated intensity halfway between \( s' \) and its neighboring pixel to the left, right, top and bottom, respectively, and \( \sigma_f \) is the image noise variance that depends on the quality of input pictures.

The next step is to fuse the disparity map \( D \) and the left motion field \( M_L \) to estimate the right motion field \( M_R \). As shown in Fig. 3 (b), the 3D motion vector can be decomposed into three components: horizontal motion \( V_h \) that is parallel to \( oLh \), vertical motion \( V_v \) that is perpendicular to the \( oLh \) plane, and parallel motion \( V_p \) that is perpendicular to both \( V_h \) and \( V_v \) (which is ignored in the motion fusion algorithm).

Denote \( F \) as the focal length of both cameras, \( B \) as the base line distance \( oLh \) between two cameras, \( S \) as the pixel size in the imaging plane, and \( D \) as the convergence distance. The stereo scene geometry is illustrated in Fig. 3 (a). The stereo motion fusion algorithm has the following steps (see block diagram in Fig. 3 (c)).

1) Estimating the depth. Calculate angles \( \alpha, \beta \) using the horizontal coordinate of the pixel \( s \). Then the depth of \( s \) is \( H_p = B \cdot \frac{1}{(\tan(\alpha))^2 + (\tan(\beta))^2} \).

2) Estimating the right horizontal motion vector \( v^r_h = V^r_h l_p / l_p \) based on the depth \( H_p \) and the left horizontal motion vector \( v^r_h = V^r_h l_p / l_p \) using (note that \( V^r_h = V^r_h \)).

\[
\frac{v^r_h}{l_p} = \frac{V^r_h l_p}{l_p} = \frac{\sin(\alpha + \frac{\theta}{2}) \sin(\beta)}{\sin(\beta + \frac{\theta}{2})} \sin(\alpha), \quad (4)
\]

3) Estimating the right vertical motion vector using

\[
\frac{v^r_v}{v^r_h} = \frac{\sin(\alpha + \frac{\theta}{2}) \sin(\beta)}{\sin(\beta + \frac{\theta}{2})} \sin(\alpha), \quad (5)
\]

V. SWC OF MOTION VECTORS AND WZC OF RESIDUAL COEFFICIENTS

In SWC of \( M^R_k \) and WZC of \( X_k \) based on the decoder side informations \( M^R_k \) and \( Y_k \), respectively, the key requirement is the correlation model. However, unlike ideal sources (e.g., i.i.d. jointly Gaussian), this correlation is not available \textit{a priori}. As in other works on distributed video coding in the literature (e.g., [18]), we collect joint statistics from training video sequences between each source-side information pair to build a generic correlation model.

Then the Wyner-Ziv encoder quantizes \( X_k \) using scalar quantization. The resulting quantization levels and the motion

VI. SIMULATION RESULTS

In our simulations, we use the Y-component of the 720 × 288 “tunnel” stereo video sequences. Both the left and right sequences are coded by H.264 standard, coding parameters and the statistics of the resulting bitstream for both the low-rate case and the high-rate case are given in Table I.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Low-rate regime</th>
<th>High-rate regime</th>
</tr>
</thead>
<tbody>
<tr>
<td>QP I frame</td>
<td>35</td>
<td>22</td>
</tr>
<tr>
<td>QP P frame</td>
<td>33</td>
<td>20</td>
</tr>
<tr>
<td>Total frames</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Inter-search mode</td>
<td>16 × 16, 16 × 8, 8 × 16</td>
<td>16 × 16, 16 × 8, 8 × 16</td>
</tr>
<tr>
<td>Motion precision</td>
<td>quarter-pel</td>
<td>quarter-pel</td>
</tr>
<tr>
<td>Statistics</td>
<td>Low-rate regime</td>
<td>High-rate regime</td>
</tr>
<tr>
<td>Bit rate</td>
<td>6.006 Kbps</td>
<td>6.006 Kbps</td>
</tr>
<tr>
<td>Average SNR</td>
<td>31.15 dB</td>
<td>40.59 dB</td>
</tr>
</tbody>
</table>

The disparity maps and motion fields are generated in half-pel precision by the modified stereo matching algorithm described in Section IV. The parameter values are consistent with those in [15]: \( \epsilon_d = 0.01, \sigma_d = 8, \epsilon_p = 0.05, \sigma_p = 0.6 \). We also incorporate segmentation results produced by the mean-shift algorithm [19].

In low-rate case, only the motion vectors for the inter-coded blocks are Slepian-Wolf coded based on the side information...
generated at the decoder. Using the joint statistics collected from all 20 frames of “tunnel” sequence as generic correlation model, and a multilevel Slepian-Wolf code implemented by LDPC codes, we are able to save 3,747 bits from the 38,970 motion vector bits in the right bitstream. All the other components are directly transmitted to the decoder. Figs. 4 compare the rate-distortion performance for separate encoding, MT coding, and joint encoding of “tunnel” stereo video sequences, where in the joint encoding case we interleave the left and right stereo video sequences and use H.264 to code the interleaved sequence with two reference frames in motion estimation, to generate a benchmark for MT video coding.

In high-rate case, we implement the algorithms described in Section III for the I-frame (with $P_l = 34$ and $P_h = 22$) and in Section IV for the residual coefficients of the P-frames. Generic correlation models between the sources and the side informations are generated based on the joint statistics collected from all 20 frames of “tunnel” sequence. Scalar quantization followed by LDPC code based multilevel Slepian-Wolf codes are employed for Wyner-Ziv coding. The total saving is 32,548 bits, which is equivalent to 48.8 Kbps, or 0.75% of the total bit rate. Again, a performance comparison among separate encoding, MT coding, and joint encoding is shown in Fig. 5.

However, compared to separate H.264 compression, the computational complexity of our scheme is higher, and most of the computation time is spent on the stereo matching algorithm (which takes around 40 minutes per frame on a Pentium IV 2.0GHz PC).

VII. CONCLUSION

In this paper, we addressed MT video coding that targets at saving the sum rate over separate monocular video compressions with H.264. The main idea is to explore the binocular redundancy by using disparity maps generated by stereo matching to form side informations in WZC. Results on rate savings for motion vectors in the low-rate regime and for I-frame and residual coefficients in the high-rate regime are given.