# Model-Based Joint Source Channel Coding for Subband Video

Mingshi Wang and Mihaela van der Schaar

*Abstract*—**The objective of joint source channel coding (JSCC) is to optimally allocate the available channel bandwidth between source coding and channel coding in order to minimize the average distortion in the presence of packet losses. Unlike previous research, which focuses on determining distortion-optimized methods for JSCC using either assumptions about the rate-distortion (R-D) curve properties of source data (e.g., convexity) or experimental R-D data, we explicitly employ the analytical operational R-D model of a three-dimensional wavelet video coder to solve the JSCC problem. Using this model, we formulated the JSCC optimization as a nonlinear programming (NP) problem. By expressing the NP problem in terms of a dynamic programming equation, we derived the necessary conditions that facilitate the search for global optimal solutions. In this letter, we focus on finding the optimal JSCC problem for subband video coding and not on deriving computationally efficient methods for JSCC.**

*Index Terms*—**Joint source channel coding (JSCC), nonlinear programming (NP), operational rate-distortion (R-D) model, three-dimensional (3-D) wavelet subband coding.**

## I. Introduction

The GOAL of joint source channel coding (JSCC) is to minimize the average distortion experienced by a compressed bitstream in the presence of packet losses by optimally allocating the total coding bit budget $R_t$ between source and channel coding. A video packet is considered to be lost if transmission errors are detected and cannot be corrected at the lower layers of the protocol stack. In this letter, we assume that the application-layer knows when a packet is in error based on the information provided by lower physical and/or MAC retransmission layer protocols. Let $R_s$ and $R_c$ denote the source and channel coding bits for a three-dimensional (3-D) wavelet video coding bitstream, subject to the constraint $R_s + R_c = R_t$, and let the incurred distortion be $D(R_s; R_c)$. It is well known that a tradeoff exists between $R_s$ and $R_c$. If more coding bits are devoted to $R_s$, then the source coding distortion, i.e., the quantization distortion, is reduced at the cost of increased probability of packet loss, and vice versa. The objective of JSCC is to find the optimal value of $R_s$ for which $D(R_s; R_c)$ is minimized. We illustrate this tradeoff in the example depicted in Fig. 1. In this example, the Mobile sequence at CIF resolution was coded using the 3-D ESCOT codec [8]. The rate-distortion (R-D) function

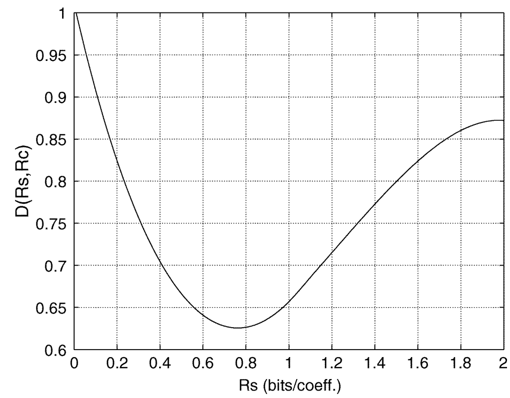


Fig. 1. Example that plots the subband distortion $D(R_s, R_c)$ as a function of source coding bit-rate $R_s$ subject to the constraint $R_s + R_c = 2$ (bits/coeff.). The distortion is normalized to its maximum value. The optimal value of $R_s$ minimizes the average distortion $D(R_s, R_c)$.

was plotted for the subband at the lowest resolution, which was protected by a systematic Reed–Solomon code. The subband distortion was normalized to the signal variance. The channel was characterized by a packet loss rate of 9.97% and a burst length of 9.57. These parameters were chosen to be consistent with the simulations done in [4]. From the figure, it can be concluded that the distortion is minimized when the source coding rate is around 0.8 (bits/coeff.).

Unlike existing JSCC research that uses operational R-D curve interpolated from experimental data [2], [5]–[7], [9], we proceed from the explicit analytical operational R-D model [12] to solve the JSCC problem as an NP problem. The source coding bit-rate and distortion of a subband have been shown to be functions of the quantization parameters and the signal variances [12]. The corresponding subband signal varainces are easily calculated during the encoding stage.

Besides giving insight into the properties of the JSCC solution, this approach has the advantage that, unlike the Lagrangian multiplier method that is only limited to operating points on the convex hull, the proposed dynamic programming solution can use the overall operational R-D characteristics of subband video coders. The dynamic programming is performed in terms of both amplitude resolution (SNR scalability) and spatial/temporal scalability. Hence, spatial-temporal subbands can be fully discarded (i.e., not transmitted) and the bit-rate can be allocated to the source or channel coding of alternative subbands based on the result of the optimization.

By rewriting the NP problem in the form of dynamic programming, we derive the necessary conditions for the global optimal solution, which is then used as the nonlinear constraint to reduce the searching range. Note that our goal is not to determine a more computationally efficient solution for the JSCC of 3-D wavelet video but rather to derive an analytical solution for this problem by using operational R-D models.

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The letter is organized as follows. In Section II, we formulate and analyze the JSCC problem using our previously derived analytical R-D model. Section III presents the simulation results, and Section IV summarizes our conclusion and the future research.

## II. Analytical Solution for JSCC Based on Operational R-D

### A. Formulation of JSCC Problem

Assume a video sequence is compressed in $K$ spatial-temporal subbands, and let $\tau, 0 \leqslant \tau \leqslant K-1$ be the index of these subbands. Denote the quantization parameter and channel code as $\boldsymbol{\Delta} = [\Delta_0, \cdots, \Delta_{K-1}] \in \Re^K$, $\mathbf{C} = [C_0, \cdots, C_{K-1}], C_\tau \in \mathcal{C}_\tau$, respectively, where $\mathcal{C}_\tau$ is the admissible channel code family for subband $\tau$. Let $\mathbf{g}$ be the JSCC policy, i.e., $\mathbf{g} = [g_0, \cdots, g_{K-1}]$, where $g_\tau \triangleq [\Delta_\tau, C_\tau] \in \Re \times \mathcal{C}_\tau$. The following analysis assumes 3-D embedded subband coding [8], where the coefficients in different subbands are coded and packetized independently to preserve the spatial-temporal scalability. The subband coding distortion is independent of each other, and therefore, the expectation of the overall distortion $E[D_K](\mathbf{g})$ is

$$\begin{aligned}\mathrm{E}[D_K](\mathbf{g}) &= \mathrm{E}\left[\sum_{\tau=0}^{K-1} \mathrm{s}(\tau) G_\tau \mathrm{d}_\tau\left(\Phi(X_\tau), g_\tau\right)\right] \\ &= \sum_{\tau=0}^{K-1} \mathrm{s}(\tau) G_\tau \mathrm{E}\left[\mathrm{d}_\tau\left(\Phi(X_\tau), g_\tau\right)\right] \end{aligned} \tag{1}$$

where $\mathrm{s}(\tau)$ is the fraction of the total number of wavelet coefficients $X_\tau$ in subband $\tau$, $G_\tau$ is the synthesis gain, and $\mathrm{d}_\tau(\Phi(X_\tau), g_\tau)$ is the distortion per coefficient in subband $\tau$, which is a function of the source statistic characteristics $\Phi(X_\tau)$, the quantization parameter $\Delta_\tau$, and the associated channel code $C_\tau$. The expectation of subband distortion $\mathrm{d}_\tau$ can be evaluated by taking the average on its conditional expectations

$$\mathrm{E}\left[\mathrm{d}_\tau\left(\Phi(X_\tau), g_\tau\right)\right] = \varepsilon_\tau\left(\Phi(X_\tau), \Delta_\tau\right)\left(1 - P(C_\tau)\right) + \sigma_\tau^2 P(C_\tau). \tag{2}$$

In the above equation, $P(C_\tau)$ denotes the effective packet loss rate under the protection of channel code $C_\tau$. $P(C_\tau)$ represents the ratio of unrecoverable packets after decoding and hence is different from the channel packet loss rate. $\varepsilon_\tau(\Phi(X_\tau), \Delta_\tau)$ is the source coding distortion due to the quantization noise; $\sigma_\tau^2$ is the variance of $X_\tau$, which is equal to the distortion if the whole packet is lost in the transmission.

The total coding rate for the subband is the sum of the source coding bits and the channel coding bits. If the source coding rate equals $\mathcal{R}_\tau(\Phi(X_\tau), \Delta_\tau)$, then the total coding rate equals

$$R_K(\mathbf{g}) = \sum_{\tau=0}^{K-1} \mathrm{s}(\tau) \frac{\mathcal{R}_\tau\left(\Phi(X_\tau), \Delta_\tau\right)}{\mathrm{r}(C_\tau)} \tag{3}$$

where $\mathrm{r}(C_\tau)$ is the code rate of $C_\tau$. Given the overall rate budget $R$, the JSCC problem can be formulated as

$$D_K^*(R) = \inf_{\{\mathbf{g} | R_K(\mathbf{g}) \leqslant R\}} \mathrm{E}[D_K](\mathbf{g}). \tag{4}$$

### B. Properties of the JSCC Solution for Subband Video

Clearly, the JSCC in (4) is an NP problem, which becomes very complicated, especially when the number of subbands increases. Therefore, it is necessary to reduce the possible solutions search space by using specific properties of the optimal solutions. Problem (4) can be solved using the Lagrange multiplier, as proposed in [6]. However, in this letter, we will determine the solution using dynamic programming (as in [5]). For this purpose, we rewrite (1) and (3) recursively in terms of the partial summation

$$\begin{cases} D_{k+1} = D_k + \mathrm{s}(k) G_k \mathrm{E}\left[\mathrm{d}_k\left(\Phi(X_k), g_k\right)\right] \\ R_{k+1} = R_k + \mathrm{s}(k) \frac{\mathcal{R}_k(\Phi(X_k), \Delta_k)}{\mathrm{r}(C_k)} \end{cases} \quad k = 1, 2, \cdots, K-1. \tag{5}$$

It should be noted that the subscript in the above equation is $k$ instead of $\tau$, since $\tau$ is the index of the subbands, while $k$ denotes the number of subbands that appear in the partial summation, i.e., $D_k = \sum_{\tau=0}^{k-1} \mathrm{s}(\tau) G_\tau \mathrm{E}[\mathrm{d}_\tau(\Phi(X_\tau), g_\tau)$ and $R_k = \sum_{\tau=0}^{k-1} \mathrm{s}(\tau) \mathrm{R}_\tau(\Phi(X_\tau), \Delta_\tau)/\mathrm{r}(C_\tau)$. Equation (5) implies that the solution to the optimum JSCC problem (4) contains the solutions to the optimum subproblems, as expressed by the following theorem.

*Theorem 1:* Let $\mathbf{g}^*(0:k-1) \triangleq [g_0^*, \cdots, g_{k-1}^*]$ be the optimal policy such that $D_k$ reaches the infimum $D_k^*(R)$ subject to the constraint $R_k \leqslant R$

$$D_k^*(R) = \inf_{\{\mathbf{g}^*(0:k-1) | R_k \leqslant R\}} D_k. \tag{6}$$

Then $D_k^*(R)$ satisfies the following dynamic programming equation

$$\begin{aligned} D_{k+1}^*(R) = \inf_{g_k \in \Re \times \mathcal{C}_k} &\left\{ \mathrm{s}(k) G_k \mathrm{E}\left[\mathrm{d}_k\left(\Phi(X_k), g_k\right)\right] \right. \\ &\left. + D_k^*\left(R - \mathrm{s}(k) \frac{\mathcal{R}_k\left(\Phi(X_k), \Delta_k\right)}{\mathrm{r}(C_k)}\right) \right\} \quad k = 1, 2, \cdots K-1. \end{aligned} \tag{7}$$

The proof is straightforward and will not be given here. The distortion function $D_k^*(R)$ is always a convex monotonically decreasing function. The property of convexity of the R-D function can be derived from its definition in terms of the mutual information between the source and its approximation. Based on this property, the following corollary can be derived.

*Corollary 1:* Assume $\mathbf{g}^*(0:k-1) = [g_0^*, \cdots, g_{k-1}^*]$ is the optimal policy in order to minimize $D_k$ subject to the constraint $R_k \leqslant R$; then the optimal value $D_k^*$ satisfies the following differential equations:

$$\frac{\partial D_{k+1}^*(R)}{\partial R} = D_k^{*\prime}\left(R - \mathrm{s}(k) \frac{\mathcal{R}_k\left(\Phi(X_k), \Delta_k^*\right)}{\mathrm{r}\left(C_k^*\right)}\right) \tag{8}$$

with the constraint

$$\begin{aligned} &\mathcal{T}\left(C_k^*\right) G_k \frac{\partial \varepsilon_k\left(\Phi(X_k), \Delta_k^*\right)}{\partial \Delta_k^*} \\ &\quad = D_k^{*\prime}\left(R - \mathrm{s}(k) \frac{\mathcal{R}_k\left(\Phi(X_k), \Delta_k^*\right)}{\mathrm{r}\left(C_k^*\right)}\right) \frac{\partial \mathcal{R}_k\left(\Phi(X_k), \Delta_k^*\right)}{\partial \Delta_k^*} \end{aligned} \tag{9}$$

for $k=1,2,\cdots,K-1$, where $\mathcal{T}(C_k) \triangleq \mathrm{r}(C_k)(1-P(C_k))$.

*Proof:* Let $g_k^* = [\Delta_k^*, C_k^*]$ be the optimal policy to minimize the quantity in the right-hand side bracket of (7); then $\Delta_k^*$ and $C_k^*$ must satisfy the following equations:

$$\frac{\partial}{\partial \Delta_k}\left\{\mathrm{s}(k)G_k\mathrm{E}\left[\mathrm{d}_k\left(\Phi(X_k),g_k\right)\right]+ D_k^*\left(R-\mathrm{s}(k)\frac{\mathcal{R}_k\left(\Phi(X_k),\Delta_k\right)}{\mathrm{r}(C_k)}\right)\right\}=0 \quad (10)$$

$$\frac{\partial}{\partial \mathrm{r}(C_k)}\left\{\mathrm{s}(k)G_k\mathrm{E}\left[\mathrm{d}_k\left(\Phi(X_k),g_k\right)\right]+ D_k^*\left(R-\mathrm{s}(k)\frac{\mathcal{R}_k\left(\Phi(X_k),\Delta_k\right)}{\mathrm{r}(C_k)}\right)\right\}=0. \quad (11)$$

Substituting (2) into (10) and (11) yields the constraint (9), from which we can solve the optimal values $g_k^* = [\Delta_k^*, C_k^*]$. Differentiating both sides of (7) with respect to $R$ and substituting $\Delta_k^*$, $\mathrm{r}(C_k^*)$ into it gives the final result (8). ■

Corollary 1 reveals that in the optimal JSCC design, all the partial summations $D_k^*$ have equal slopes with respect to the total coding bit-rate $R$. This also implies that each single subband has an equal slope with respect to its coding rate. The conclusion is consistent with previous R-D research results where an optimization problem is decomposed into independent subproblems, which have equal Lagrangian multipliers at the optimum point. For example, the optimal rate allocation scheme states that when the overall source coding distortion is minimized under the coding bit-rate constraint, the distortion for all the subbands should have the same slope [8], [11]. Our contribution is that we have arrived at this conclusion using dynamic programming equations.

### C. Solutions to JSCC Problems Using Operational R-D Model

The solution to the optimal JSCC problem is now obtained given the analytical expression of the operational R-D function $\varepsilon_\tau(\Phi(X_\tau),\Delta_\tau)$ and $\mathcal{R}_\tau(\Phi(X_\tau),\Delta_\tau)$. It is already known that the ac subbands can be modeled as Laplacian sources, whereas the dc subband is modeled as a Gaussian source [3]. Based on this fact, the operational R-D model can be formulated by the following equations [12]:

$$\varepsilon_\tau\left(\Phi(X_\tau),\Delta_\tau\right)=\mathrm{g}\left(\frac{\Delta_\tau}{\sigma_\tau}\right)\sigma_\tau^2 \quad (12a)$$

$$\mathcal{R}_\tau\left(\Phi(X_\tau),\Delta_\tau\right)=\alpha_R \mathrm{e}^{-\beta\frac{\Delta_\tau}{\sigma_\tau}} \quad (12b)$$

for ac subbands, and

$$\varepsilon_\tau(\mathcal{R}_\tau)\cong \mathrm{f}(\mathcal{R}_\tau)(1-r)\sigma_\tau^2 2^{-2\mathcal{R}_\tau} \quad (13)$$

for the dc subband. In the above equations

$$\mathrm{g}(\nu)=-\rho\left(\nu+\frac{1}{\sqrt{2}}\right)^2+1-\frac{\rho^2\nu^2}{(1-\rho)^2}$$
$$\rho \triangleq \mathrm{e}^{-\sqrt{2}\nu} \quad (14)$$

is the subband quantization distortion normalized to the signal variance $\sigma_\tau^2$; $\alpha_R \cong 4.2469$ and $\beta \cong 1.3102$ are both constants; $\mathrm{f}(\mathcal{R}_\tau)\cong 1$ for Gaussian source and $r \cong 0.95$ for images with smooth textures [1]. The statistic characteristics of the subband source $\Phi(X_\tau)$ is captured by the signal variance $\sigma_\tau^2$. This is only a first-order approximation to ease the computation complexity, since $\Phi(X_\tau)$ is generally represented by the histogram of the subband coefficients.

When $\tau=0,1,\cdots,K-1$ refers to the ac subband. Combining (12) and (13) with (8) and (9) yields the following results:

$$\frac{\partial D_{k+1}^*(R)}{\partial R}=-G_k\mathcal{A}\mathcal{T}\left(C_k^*\right)\nu_k^{*\gamma}\sigma_k^2 \quad k=0,1,\cdots,K-1. \quad (15)$$

When $\tau=0$ refers to a dc subband, and $\tau=1,2,\cdots,K-1$ refers to the ac subbands, the above equation remains the same, except for $k=0$, which is

$$\frac{\partial D_1^*(R)}{\partial R}=-2\ln 2\cdot(1-r)G_0\mathcal{T}\left(C_0^*\right)\sigma_0^2 2^{-2\mathcal{R}_0(\Phi(X_0),\Delta_0^*)}. \quad (16)$$

In the above two equations, $\mathcal{A}=\alpha_g/\alpha_R\beta$ is a constant; $\alpha_g \cong 1.3474$; $\gamma \cong 1.6853$; and $\nu \triangleq \Delta/\sigma$ is the quantization parameter normalized to the signal variance. In the above derivation, we have used the approximate equality $\mathrm{g}'(\nu)\cong \alpha_g\nu^\gamma \mathrm{e}^{-\beta\nu}$ [12], and (16) is obtained by using Lagrange multipliers.

By examining corollary 1, we concluded that in order to minimize the total coding distortion, the quantization parameter $\Delta_\tau$ and channel code $C_\tau$ should be chosen such that the right-hand side of (15) and (16) is equal to a constant. Therefore, the JSCC problem can be reformulated by the following corollary.

*Corollary 2:* Let the subband JSCC problem be described by (4), and denote $\mathbf{g}^*$ as the optimal policy; then the JSCC problem is equivalent to the following nonlinear constraint optimization:

$$\mathbf{g}^*=\arg\min_{\mathbf{g}}\mathrm{E}[D_K](\mathbf{g}) \quad (17)$$

subject to the nonlinear inequality constraint

$$\sum_{\tau=0}^{K-1}\frac{\mathrm{s}(\tau)}{\mathrm{r}(C_\tau)}\mathrm{e}^{-\beta\nu_\tau}\leqslant\frac{R}{\alpha_R} \quad (18)$$

and the nonlinear equality constraint

$$G_\tau\mathcal{T}(C_\tau)\nu_\tau^\gamma\sigma_\tau^2=G_{\tau-1}\mathcal{T}(C_{\tau-1})\nu_{\tau-1}^\gamma\sigma_{\tau-1}^2 \quad \tau=2,3,\cdots,K-1 \quad (19a)$$

$$G_1\mathcal{T}(C_1)\nu_1^\gamma\sigma_1^2=G_0\mathcal{T}(C_0)\nu_0^\gamma\sigma_0^2 \quad \text{when } \tau=0 \text{ refers to ac subband.} \quad (19b)$$

$$G_1\mathcal{T}(C_1)\nu_1^\gamma\sigma_1^2=2\ln 2\frac{\alpha_R\beta(1-r)}{\alpha_g}G_0\mathcal{T}(C_0)\times\sigma_0^2 2^{-2\mathcal{R}_0(\Phi(X_0),\Delta_0)} \quad \text{when } \tau=0 \text{ refers to dc subband.} \quad (19c)$$

Using the analytical expression of $P(C)$ given in [10], it is found that $\mathcal{T}(C)$ is a monotonically increasing function of the coding rate $r(C)$. Combining this observation with the constraint (19) demonstrates the tradeoff between the source coding rate and the channel coding rate. Meanwhile, the search range for the global optimal solution is significantly reduced by the constraint (19).

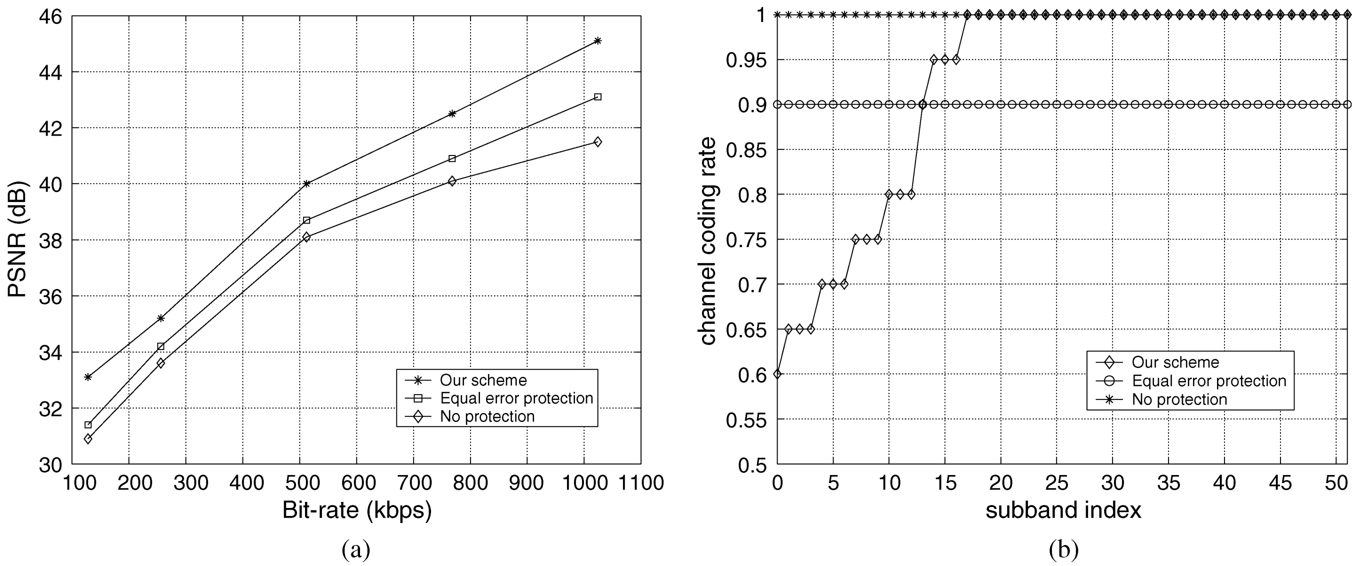


Fig. 2. JSCC example for the Akiyo sequence. (a) Comparison of the R-D performance for our algorithm, EEP, and NEP. (b) Assignment of channel code rate r for different subbands after JSCC optimization.

## III. Example of JSCC Based on Operational R-D Model

We applied the proposed JSCC solution to the 3-D ESCOT coder [8] for the Akiyo video sequence at CIF resolution. The packet loss rate for the channel is 9.97%. However, a thorough investigation of the JSCC performance of this coder is beyond the scope of this letter, which was solely aimed at deriving analytically the optimal JSCC solution. In our example, the Daubechies 5/3 filters were used to decompose the video sequences temporarily and spatially. Specifically, we first performed the three-level dyadic temporal decomposition, followed by a four-level 2-D spatial decomposition within each temporal subband. The total number of subbands equals 52. Similar results could have been derived for alternative decomposition structures and filter types. The subbands are packetized and protected by the systematic Reed–Solomon code. The simulation results are shown in Fig. 2(a), where the R-D performance after JSCC optimization by the method in this letter was compared against that for equal error protection (EEP) and no error protection (NEP). For the EEP scheme, all the subbands are protected with an equal channel code rate of 0.9, and for the NEP scheme, all the subbands are left unprotected. It is seen that the optimal JSCC achieves a gain of approximately 1.5 dB over the EEP scheme and more than 2 dB over the NEP scheme. The resulting optimal channel code rate assignment for subbands is plotted in Fig. 2(b), together with the channel code rate assignment for EEP and NEP schemes. The total bit-rate budget is 870 (kbps). The subbands are indexed from the coarsest in the lowest temporal band to the finest in the highest temporal band.

## IV. Conclusion and Future Research

Based on the analytical R-D model, the optimal JSCC problem is formulated as a nonlinear optimization problem that can be solved using dynamic programming. The properties of the optimal JSCC solution are derived from the dynamic programming equation and utilized to restrict the search range so that the possibility of finding global optimal solutions is enhanced. Since solving nonlinear optimization problems usually entails heavy computations, quantifying the complexity of this approach and finding efficient algorithms constitute an important topic for our future research.

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