On Error Resilient Design of Predictive Scalable Coding Systems

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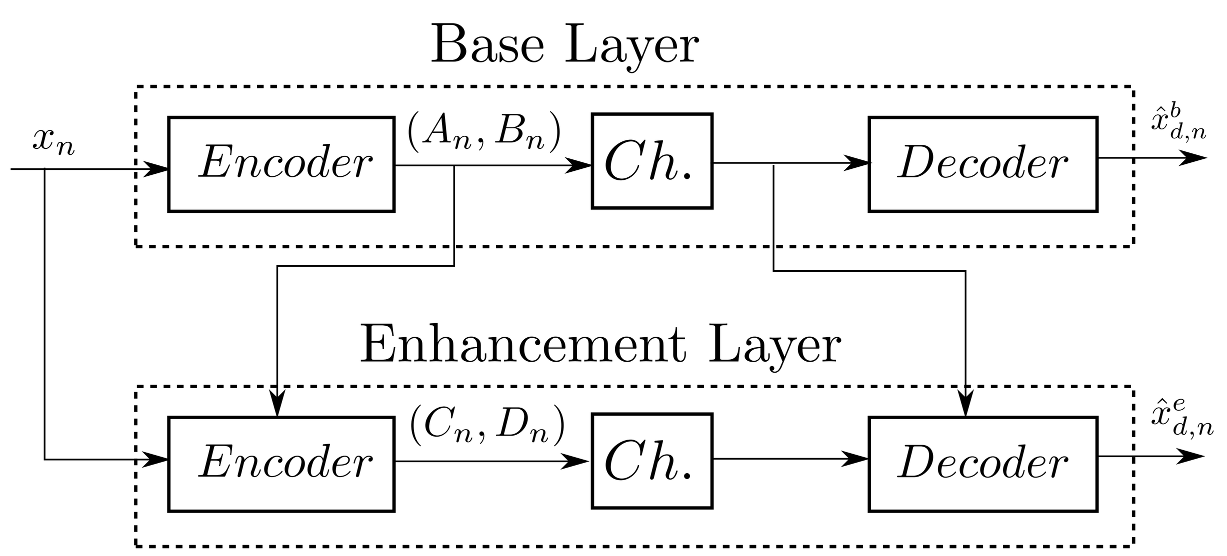
Scalable Coder Architecture and Problem Statement

- Scalable coding framework considers hierarchical bitstream (layers).
- Lower information bitstream is embedded into a higher information bitstream in a way that minimizes redundancy.
- Without loss of generality, we consider a two-layer predictive scalable coder.



- We propose a novel technique for designing scalable coder predictors and quantizers at all layers that aims for:
  - Accounting for channel uncertainty due to potential packet loss.
  - Utilizing all available information at a given layer by designing the system components within estimation-theoretics framework.

Base-Layer Operation

- First order linear predictor with prediction coefficient α_b.
- The base layer predictions are based on expected decoder reconstructions,

$$\tilde{x}^b_{e,n} = \alpha_b \mathbb{E}\left\{\hat{x}^b_{d,n-1}\right\}. \quad (1)$$

- End-to-end distortion (EED) estimation can be expressed as,

$$\mathbb{E}\{D_b\} = \sum_{n=0}^{N-1} x_n^2 - 2x_n \mathbb{E}\left\{\hat{x}^b_{d,n}\right\} + \mathbb{E}\left\{\left(\hat{x}^b_{d,n}\right)^2\right\}. \quad (2)$$

- The base layers packets are assumed to be lost independently with probability p_b.
- EED moments can be recursively updated as,

$$\mathbb{E}\left\{\hat{x}^b_{d,n}\right\} = (1-p_b)\hat{e}^b_{e,n} + \alpha_b \mathbb{E}\left\{\hat{x}^b_{d,n-1}\right\}, \quad (3)$$

$$\mathbb{E}\left\{\left(\hat{x}^b_{d,n}\right)^2\right\} = (1-p_b)\left(\hat{e}^b_{e,n} + 2\alpha_b \mathbb{E}\left\{\hat{x}^b_{d,n-1}\right\}\right) + \alpha_b^2 \mathbb{E}\left\{\left(\hat{x}^b_{d,n-1}\right)^2\right\}. \quad (4)$$

- Optimal prediction coefficient that minimizes EED is given by,

$$\alpha_b^* = \frac{\sum_{n=0}^{N-1} \mathbb{E}\left\{\hat{x}^b_{d,n-1}\right\}\left(x_n - (1-p_b)\hat{e}^b_{e,n}\right)}{\sum_{n=0}^{N-1} \mathbb{E}\left\{\left(\hat{x}^b_{d,n-1}\right)^2\right\}}. \quad (5)$$

Enhancement Layer Operation

- The enhancement layer predictor combines current sample base layer information as well as previous enhancement layer information.

$$\tilde{x}^e_{e,n} = \mathbb{E}\left\{x_n | x_n \in \left(\tilde{x}^b_{e,n} + A_n, \tilde{x}^b_{e,n} + B_n\right), \mathbb{E}\left\{\hat{x}^e_{d,n-1}\right\}, \mathbb{E}\left\{\hat{x}^e_{d,n-2}\right\}, \dots\right\}. \quad (6)$$

- The intersection between base layer and enhancement layer quantizer intervals is then obtained as,

$$E_{d,n} = \max\left[\tilde{x}^b_{d,n} + A_n, \tilde{x}^e_{d,n} + C_n\right], \quad F_{d,n} = \min\left[\tilde{x}^b_{d,n} + B_n, \tilde{x}^e_{d,n} + D_n\right]. \quad (7)$$

- The enhancement layer packets are dropped independently with probability p_e.
- Given the current channel event, the reconstruction at the decoder can be obtained as,

$$\hat{x}^e_{d,n} = \begin{cases} \alpha_e \hat{x}^e_{d,n-1} + \bar{k}^{(E_{d,n},F_{d,n})}_{d,n} & w.p. \quad (1-p_b)(1-p_e) \\ \alpha_e \hat{x}^e_{d,n-1} + \bar{k}^{(A_{d,n},B_{d,n})}_{d,n} & w.p. \quad (1-p_b)p_e \\ \alpha_e \hat{x}^e_{d,n-1} + \bar{k}^{(-\infty,\infty)}_{d,n} & w.p. \quad p_b \end{cases} \quad (8)$$

- $\bar{k}^{(L,R)}_{d,n}$ is the centroid of the linear prediction residues in the interval (L, R).
- The EED moments at the enhancement layer can be updated recursively as,

$$\mathbb{E}\left\{\hat{x}^e_{d,n}\right\} = \mathbb{E}\left\{p_b \bar{k}^{(-\infty,\infty)}_{d,n}\right\} + \mathbb{E}\left\{p_e(1-p_b)\bar{k}^{(A_{d,n},B_{d,n})}_{d,n}\right\} + \mathbb{E}\left\{(1-p_b)(1-p_e)\bar{k}^{(E_{d,n},F_{d,n})}_{d,n}\right\} + \alpha_e \mathbb{E}\left\{\hat{x}^e_{d,n-1}\right\}, \quad (9)$$

$$\mathbb{E}\left\{\left(\hat{x}^e_{d,n}\right)^2\right\} = \mathbb{E}\left\{p_b\left(\bar{k}^{(-\infty,\infty)}_{d,n}\right)^2\right\} + \mathbb{E}\left\{p_e(1-p_b)\left(\bar{k}^{(A_{d,n},B_{d,n})}_{d,n}\right)^2\right\} + \mathbb{E}\left\{(1-p_b)(1-p_e)\left(\bar{k}^{(E_{d,n},F_{d,n})}_{d,n}\right)^2\right\} + 2\alpha_e \mathbb{E}\left\{\hat{x}^e_{d,n-1}\right\}\hat{k}_{d,n} + \alpha_e^2 \mathbb{E}\left\{\left(\hat{x}^e_{d,n-1}\right)^2\right\}, \quad (10)$$

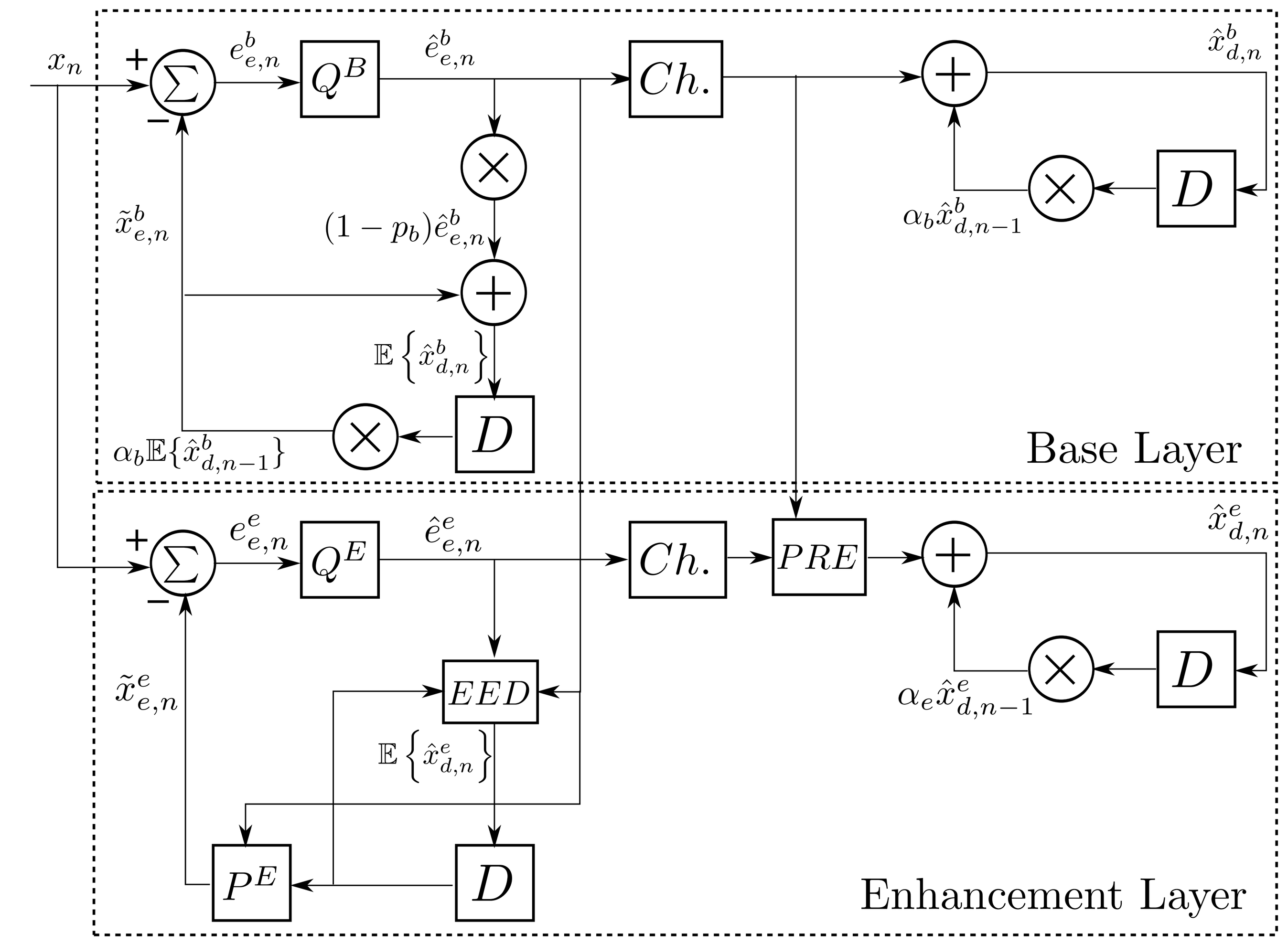
$$\hat{k}_{d,n} = p_e(1-p_b)\mathbb{E}\left\{\bar{k}^{(A_{d,n},B_{d,n})}_{d,n}\right\} + (1-p_e)(1-p_b)\mathbb{E}\left\{\bar{k}^{(E_{d,n},F_{d,n})}_{d,n}\right\} + p_b \mathbb{E}\left\{\bar{k}^{(-\infty,\infty)}_{d,n}\right\}. \quad (11)$$

- Therefore, the optimal prediction coefficient at enhancement layer, that minimizes EED, is given by,

$$\alpha_e^* = \frac{\sum_{n=0}^{N-1} \mathbb{E}\left\{\hat{x}^e_{d,n-1}\right\}\left(x_n - \hat{k}_{d,n}\right)}{\sum_{n=0}^{N-1} \mathbb{E}\left\{\left(\hat{x}^e_{d,n-1}\right)^2\right\}}. \quad (12)$$

- All entropy-constrained scalar quantizers are trained using Lloyd algorithm.
- Asymptotically closed-loop (ACL) approach, which provides the stability benefits of open-loop design while ultimately optimizing the system for closed-loop operation, is employed for designing the quantizers.

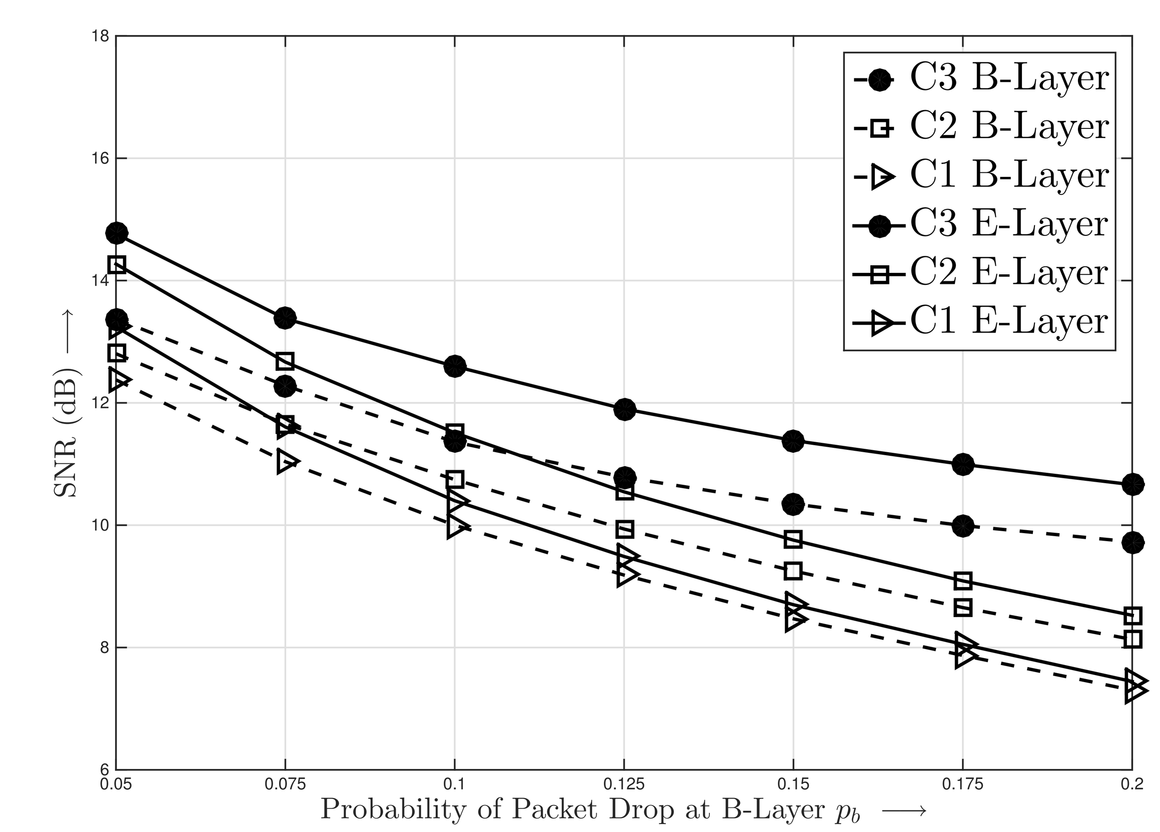
Proposed Scalable Coder Architecture



- The EED block computes the enhancement layer EED moments according to (9).
- The PRE block computes the $\bar{k}^{(L,R)}_{d,n}$, where (L, R) depends on the current channel event.

Evaluations

- We compare our proposed coder (C3) with two competing coders:
  - Coder (C1) ignores packet losses. At enhancement layers, it directly quantizes the base layers reconstruction errors.
  - Coder (C2) ignores packet losses as well. However, the enhancement layer utilizes all the available information by employing estimation-theoretics approach similar to (6).
- The proposed approach consistently outperforms its competitors, offering up to 2.2 dB and 3.3 dB gains in SNR over C2 and C1, respectively.



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