MULTIPLE FEATURE-BASED CLASSIFICATIONS ADAPTIVE LOOP FILTER (MCALF)

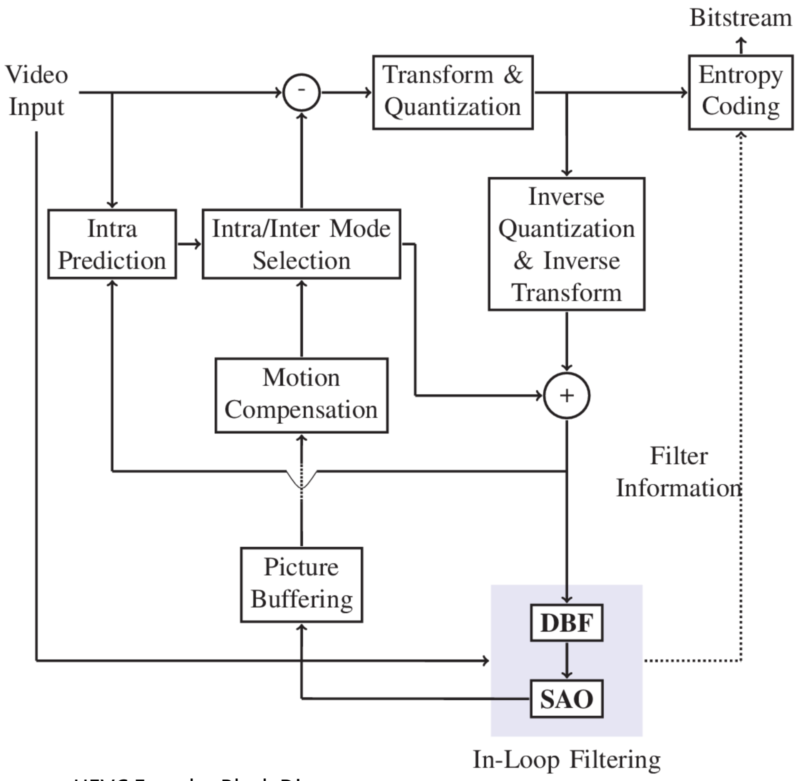
Johannes Erfurt, W. Lim, H. Schwarz, D. Marpe, T. Wiegand

Fraunhofer
HHI

CONTENT

Introduction to In-Loop Filtering

- In-loop filtering is applied after reconstruction of coding blocks
- Filtered picture is stored in decoded picture buffer and may be used for prediction



HEVC Encoder Block Diagram

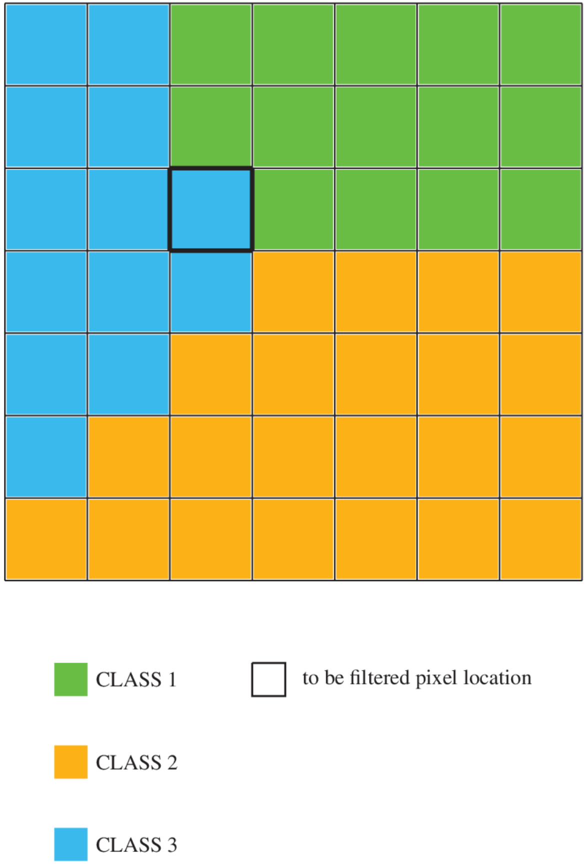
DBF = Deblockling Filter

SAO = Sample Adaptive Offset

Adaptive Loop Filtering

X = original samples, **Y** = reconstruced samples

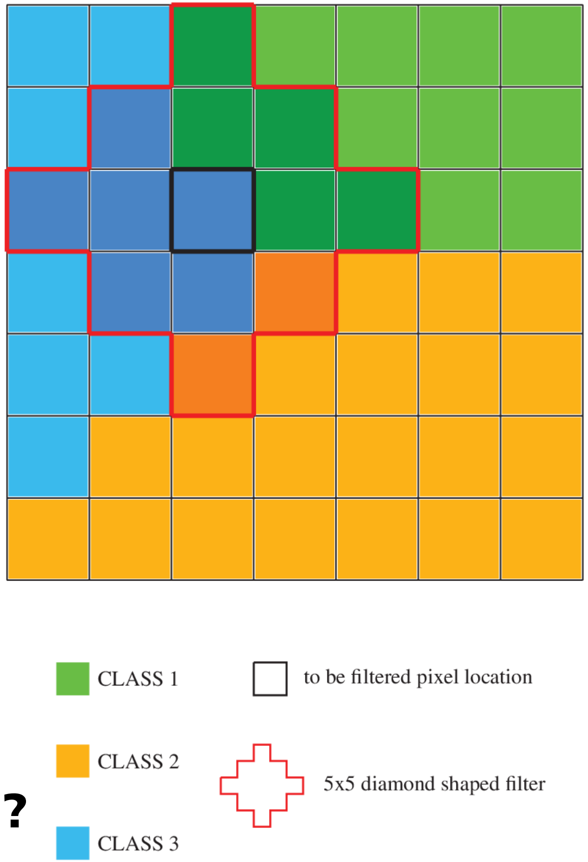
- Each pixel location is classified into one of L classes $\mathcal{C}_1, ..., \mathcal{C}_L$ based on local features
- Estimate multiple Wiener filters F_l for each $\mathcal{C}_l$, $l = 1...L$
- F_l minimizes mean square error (MSE) between X and $\tilde{X}$
- $\tilde{X} = \sum_{\ell=1}^{L} \chi_{\mathcal{C}_\ell} \cdot (Y * F_l)$ with $\chi_{\mathcal{C}_\ell}(i,j) = \begin{cases} 1, & \text{if } (i,j) \in \mathcal{C}_\ell \\ 0, & \text{otherwise} \end{cases}$



Adaptive Loop Filtering

X = original samples, **Y** = reconstruced samples

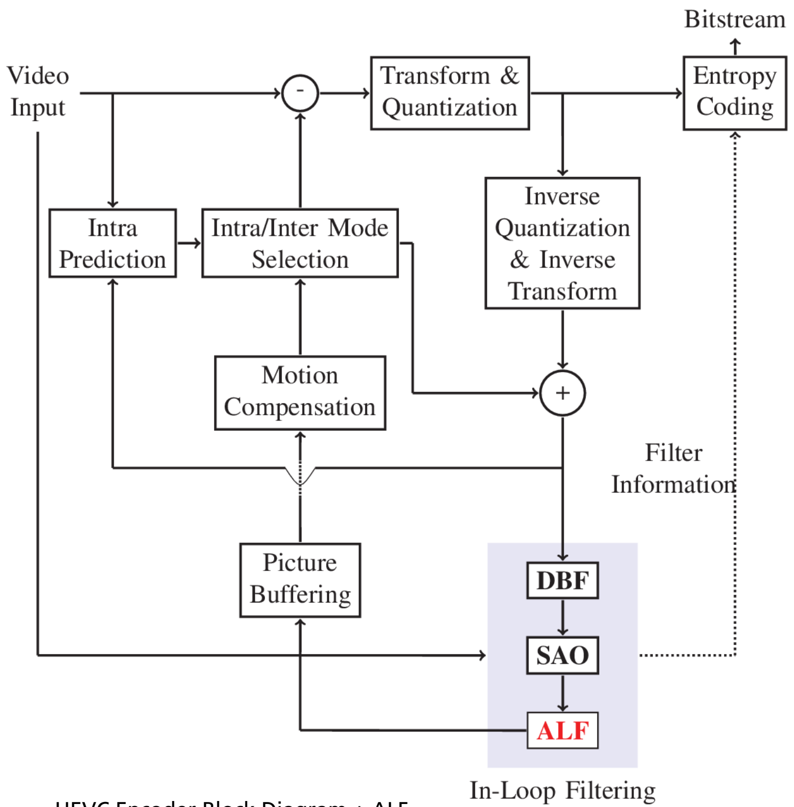
- Each pixel location is classified into one of L classes $\mathcal{C}_1, \ldots, \mathcal{C}_L$ based on local features
- Estimate multiple Wiener filters F_l for each $\mathcal{C}_l$, $l = 1 \ldots L$
- F_l minimizes mean square error (MSE) between X and $\tilde{X}$
- $$\tilde{X} = \sum_{\ell=1}^{L} \chi_{\mathcal{C}_\ell} \cdot (Y * F_l) \text{ with } \chi_{\mathcal{C}_\ell}(i,j) = \begin{cases} 1, & \text{if } (i,j) \in \mathcal{C}_\ell \\ 0, & \text{otherwise} \end{cases}$$



How do we perform classification into $\mathcal{C}_1, \ldots, \mathcal{C}_L$?

ALF and GALF

- ALF was proposed for HEVC standard and further developed resulting in GALF
- Certain coding tools make ALF/GALF very efficient:
  - Classification including directional gradients
  - Adaptively chosen filter support for each frame (5x5, 7x7, 9x9)
  - Block-wise on/off-flag
  - Temporal prediction: Use previously coded filter coefficients
  - Class merging



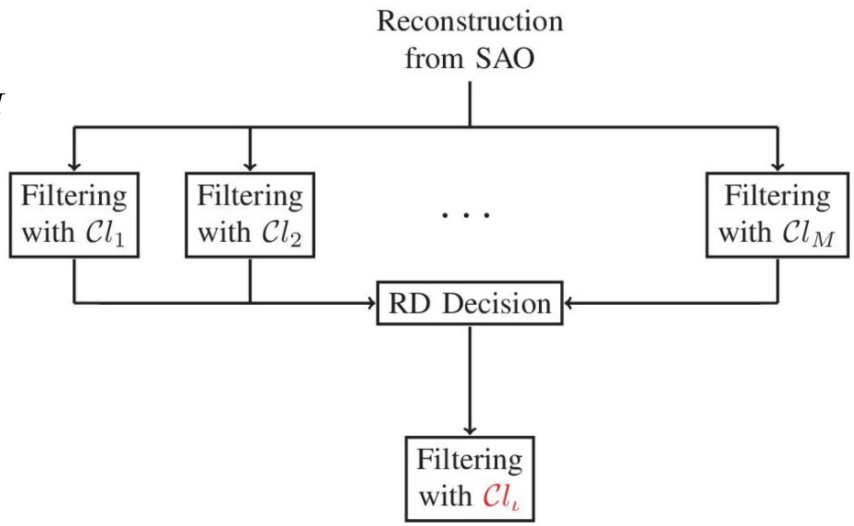
HEVC Encoder Block Diagram + ALF

Multiple Feature-based Classifications

- MCALF: Multiple Feature-based Classifications ALF
- Test at encoder side M classifiers $\mathcal{C}l_1, ..., \mathcal{C}l_M$
- Each classifier has a certain feature descriptor D to group each pixel location into classes

$$\mathcal{C}_\ell = \{(i,j) \in I : D(i,j) = \ell\} \quad \text{for } \ell = 1, \ldots, K$$

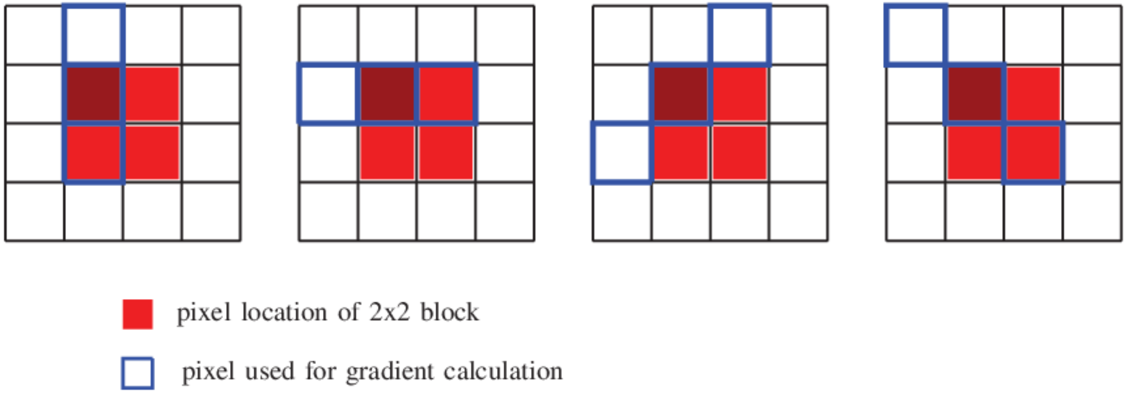
- Classifier with best RD performance chosen
- Filter index and possible filter information are signaled



Feature Descriptors

- Each classifier is descripted through different feature descriptors D
- Laplacian feature descriptor D_L : includes computation of directional gradients for squared blocks, e.g. in vertical direction:

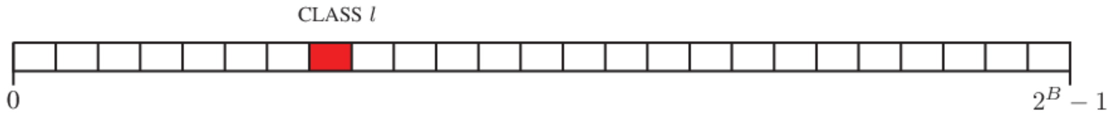
$$g(i,j) = |2 \cdot Y(i,j) - Y(i-1,j) - Y(i+1,j)|$$



Feature Descriptors

- Pixel-based feature descriptor D_P:

$$D_P(i,j) = \left\lfloor \frac{(K-1)}{2^B} Y(i,j) \right\rfloor$$ for bit depth B and K classes

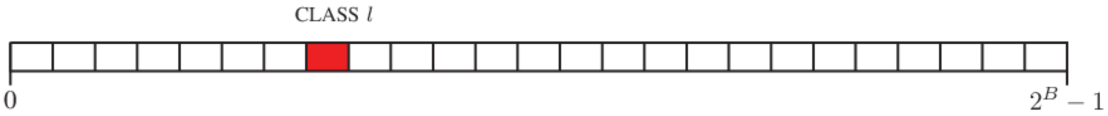


$$Y(i,j) \in [0, 2^B - 1]$$

Feature Descriptors

- Pixel-based feature descriptor D_P:

$$D_P(i,j) = \left\lfloor \frac{(K-1)}{2^B} Y(i,j) \right\rfloor$$ for bit depth B and K classes



$$Y(i,j) \in [0, 2^B - 1]$$

- Ranking-based feature descriptor D_R:

$$D_R(i,j) = \#\{(k_1,k_2) : Y(i,j) \geq Y(k_1,k_2) \text{for } |k_1 - i| \leq l, |k_2 - j| \leq h\} + 1$$

Feature Descriptors

- Product of two feature descriptors $D_1 : I \to \{1, \ldots, K_1\}$ and $D_2 : I \to \{1, \ldots, K_2\}$

$$D(i,j) = (D_1(i,j), D_2(i,j)) \in \{1, ..., K_1\} \times \{1, ..., K_2\}$$

Concept of Confidence Level

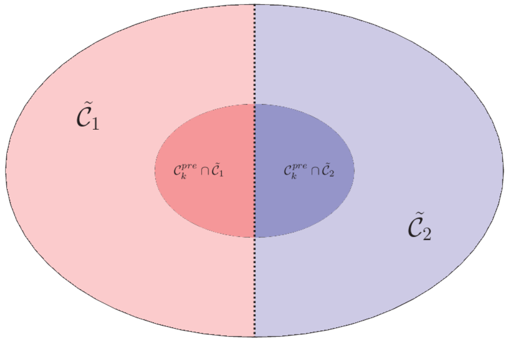
- Optimal classes for $L = 2$:

$$\tilde{C}_1 = \{(i,j) \in I : Y(i,j) \leq \mathbf{X}(i,j)\},$$
$$\tilde{C}_2 = \{(i,j) \in I : Y(i,j) > \mathbf{X}(i,j)\}$$

Concept of Confidence Level

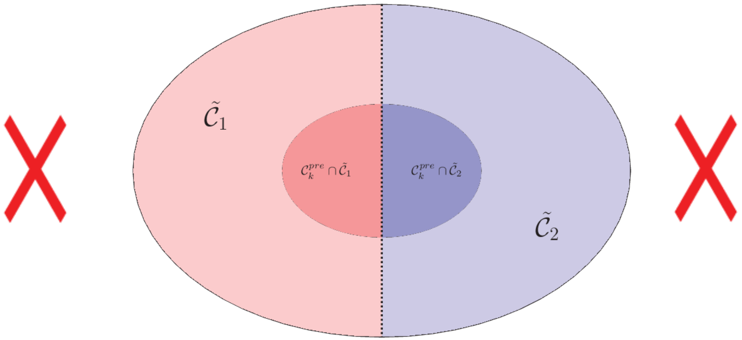
- Optimal classes for $L = 2$: $\tilde{\mathcal{C}}_1 = \{(i,j) \in I : Y(i,j) \leq \mathbf{X}(i,j)\},$

  $\tilde{\mathcal{C}}_2 = \{(i,j) \in I : Y(i,j) > \mathbf{X}(i,j)\}$
- X not available at decoder: Approximate $\tilde{\mathcal{C}}_1$ and $\tilde{\mathcal{C}}_2$
- Use certain feature descriptor D to receive K pre-classes $\mathcal{C}_1^{pre}, \ldots, \mathcal{C}_K^{pre}$



Concept of Confidence Level

- Optimal classes for $L = 2$:
$$\tilde{\mathcal{C}}_1 = \{(i,j) \in I : Y(i,j) \le \mathbf{X}(i,j)\},$$
$$\tilde{\mathcal{C}}_2 = \{(i,j) \in I : Y(i,j) > \mathbf{X}(i,j)\}$$
- X not available at decoder: Approximate $\tilde{\mathcal{C}}_1$ and $\tilde{\mathcal{C}}_2$
- Use certain feature descriptor D to receive K pre-classes $\mathcal{C}_1^{pre}, \ldots, \mathcal{C}_K^{pre}$



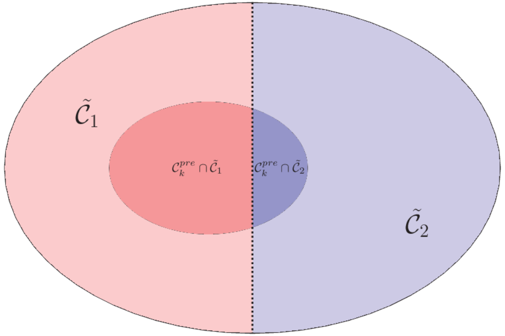
Inner ellipse should be mostly contained in left or right half

Concept of Confidence Level

- Optimal classes for $L = 2$: $\tilde{\mathcal{C}}_1 = \{(i,j) \in I : Y(i,j) \leq \mathbf{X}(i,j)\},$

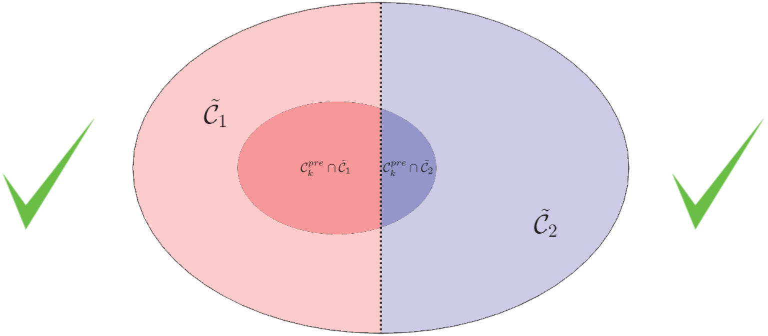
$$\tilde{\mathcal{C}}_2 = \{(i,j) \in I : Y(i,j) > \mathbf{X}(i,j)\}$$

- X not available at decoder: Approximate $\tilde{\mathcal{C}}_1$ and $\tilde{\mathcal{C}}_2$
- Use certain feature descriptor D to receive K pre-classes $\mathcal{C}_1^{pre}, \ldots, \mathcal{C}_K^{pre}$



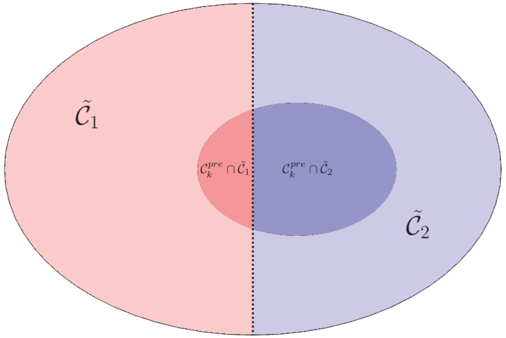
Concept of Confidence Level

- Optimal classes for $L = 2$: $\tilde{\mathcal{C}}_1 = \{(i,j) \in I : Y(i,j) \leq \mathbf{X}(i,j)\},$
  $$\tilde{\mathcal{C}}_2 = \{(i,j) \in I : Y(i,j) > \mathbf{X}(i,j)\}$$
- X not available at decoder: Approximate $\tilde{\mathcal{C}}_1$ and $\tilde{\mathcal{C}}_2$
- Use certain feature descriptor D to receive K pre-classes $\mathcal{C}_1^{pre}, \ldots, \mathcal{C}_K^{pre}$



Concept of Confidence Level

- Optimal classes for $L = 2$: $$\tilde{\mathcal{C}}_1 = \{(i,j) \in I : Y(i,j) \leq \mathbf{X}(i,j)\},$$ $$\tilde{\mathcal{C}}_2 = \{(i,j) \in I : Y(i,j) > \mathbf{X}(i,j)\}$$
- X not available at decoder: Approximate $\tilde{\mathcal{C}}_1$ and $\tilde{\mathcal{C}}_2$
- Use certain feature descriptor D to receive K pre-classes $\mathcal{C}_1^{pre}, \ldots, \mathcal{C}_K^{pre}$

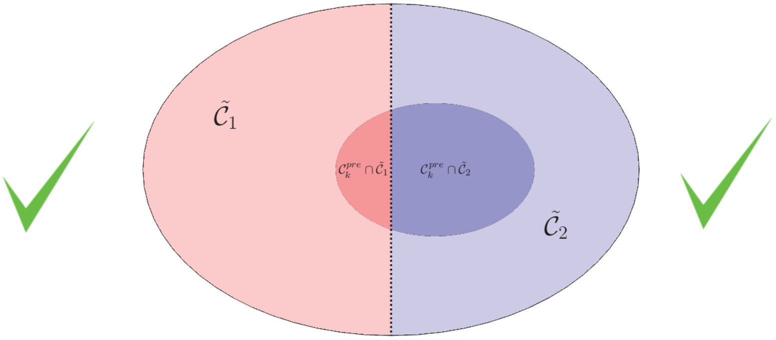


Concept of Confidence Level

- Optimal classes for $L = 2$: $\tilde{\mathcal{C}}_1 = \{(i,j) \in I : Y(i,j) \leq \mathbf{X}(i,j)\},$

$$\tilde{\mathcal{C}}_2 = \{(i,j) \in I : Y(i,j) > \mathbf{X}(i,j)\}$$

- X not available at decoder: Approximate $\tilde{\mathcal{C}}_1$ and $\tilde{\mathcal{C}}_2$
- Use certain feature descriptor D to receive K pre-classes $\mathcal{C}_1^{pre}, \ldots, \mathcal{C}_K^{pre}$



Concept of Confidence Level

- Calculate for each class $\mathcal{C}_k^{pre}$ confidence level $p_{k,1}$ and $p_{k,2}$ of D

$$p_{k,1} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_1)}{\#(\mathcal{C}_k^{pre})}, \quad p_{k,2} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_2)}{\#(\mathcal{C}_k^{pre})}$$

Concept of Confidence Level

- Calculate for each class $\mathcal{C}_k^{pre}$ confidence level $p_{k,1}$ and $p_{k,2}$ of D

$$p_{k,1} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_1)}{\#(\mathcal{C}_k^{pre})}, \quad p_{k,2} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_2)}{\#(\mathcal{C}_k^{pre})}$$

- For $p \in (1/2, 1)$ define map $P_D : \{1, \ldots, K\} \longrightarrow \{0, 1, 2\}$ with $P_D(k) = \begin{cases} 1 & p_{k,1} > p \\ 2 & p_{k,2} > p \\ 0 & \text{otherwise.} \end{cases}$

Concept of Confidence Level

- Calculate for each class $\mathcal{C}_k^{pre}$ confidence level $p_{k,1}$ and $p_{k,2}$ of D

$$p_{k,1} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_1)}{\#(\mathcal{C}_k^{pre})}, \quad p_{k,2} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_2)}{\#(\mathcal{C}_k^{pre})}$$

- For $p \in (1/2, 1)$ define map $P_D : \{1, \ldots, K\} \longrightarrow \{0, 1, 2\}$ with $P_D(k) = \begin{cases} 1 & p_{k,1} > p \\ 2 & p_{k,2} > p \\ 0 & \text{otherwise.} \end{cases}$

Concept of Confidence Level

- Calculate for each class $\mathcal{C}_k^{pre}$ confidence level $p_{k,1}$ and $p_{k,2}$ of D

$$p_{k,1} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_1)}{\#(\mathcal{C}_k^{pre})}, \quad p_{k,2} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_2)}{\#(\mathcal{C}_k^{pre})}$$

- For $p \in (1/2, 1)$ define map $P_D : \{1, \ldots, K\} \longrightarrow \{0, 1, 2\}$ with $P_D(k) = \begin{cases} 1 & p_{k,1} > p \\ 2 & p_{k,2} > p \\ 0 & \text{otherwise.} \end{cases}$

- $\mathcal{C}_\ell^e = \{(i,j) \in I : P_D(D(i,j)) = \ell\} \quad \text{for } \ell = 1, 2$ high confidence classes

Concept of Confidence Level

- Calculate for each class $\mathcal{C}_k^{pre}$ confidence level $p_{k,1}$ and $p_{k,2}$ of D

$$p_{k,1} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_1)}{\#(\mathcal{C}_k^{pre})}, \quad p_{k,2} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_2)}{\#(\mathcal{C}_k^{pre})}$$

- For $p \in (1/2, 1)$ define map $P_D : \{1, \dots, K\} \longrightarrow \{0, 1, 2\}$ with $P_D(k) = \begin{cases} 1 & p_{k,1} > p \\ 2 & p_{k,2} > p \\ 0 & \text{otherwise.} \end{cases}$

- $\mathcal{C}_\ell^e = \{(i, j) \in I : P_D(D(i, j)) = \ell\} \quad \text{for } \ell = 1, 2$ high confidence classes

Concept of Confidence Level

- Calculate for each class $\mathcal{C}_k^{pre}$ confidence level $p_{k,1}$ and $p_{k,2}$ of D

$$p_{k,1} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_1)}{\#(\mathcal{C}_k^{pre})}, \quad p_{k,2} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_2)}{\#(\mathcal{C}_k^{pre})}$$

- For $p \in (1/2, 1)$ define map $P_D : \{1, \ldots, K\} \longrightarrow \{0, 1, 2\}$ with $P_D(k) = \begin{cases} 1 & p_{k,1} > p \\ 2 & p_{k,2} > p \\ 0 & \text{otherwise.} \end{cases}$

- $\mathcal{C}_\ell^e = \{(i,j) \in I : P_D(D(i,j)) = \ell\}$ for $\ell = 1, 2$ high confidence classes

- $\mathcal{C}_\ell = \{(i,j) \notin \mathcal{C}_1^e \cup \mathcal{C}_2^e : \tilde{D}(i,j) = \ell\}$ for $\ell = 1, \ldots, \tilde{K}$ classes for remaining pixel locations

Concept of Confidence Level

- Calculate for each class $\mathcal{C}_k^{pre}$ confidence level $p_{k,1}$ and $p_{k,2}$ of D

$$p_{k,1} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_1)}{\#(\mathcal{C}_k^{pre})}, \quad p_{k,2} = \frac{\#(\mathcal{C}_k^{pre} \cap \tilde{\mathcal{C}}_2)}{\#(\mathcal{C}_k^{pre})}$$

- For $p \in (1/2, 1)$ define map $P_D : \{1, \ldots, K\} \longrightarrow \{0, 1, 2\}$ with $P_D(k) = \begin{cases} 1 & p_{k,1} > p \\ 2 & p_{k,2} > p \\ 0 & \text{otherwise.} \end{cases}$

- $\mathcal{C}_\ell^e = \{(i,j) \in I : P_D(D(i,j)) = \ell\}$ for $\ell = 1, 2$ high confidence classes

- $\mathcal{C}_\ell = \{(i,j) \notin \mathcal{C}_1^e \cup \mathcal{C}_2^e : \tilde{D}(i,j) = \ell\}$ for $\ell = 1, \ldots, \tilde{K}$ classes for remaining pixel locations

- This gives $\tilde{K} + 2$ classes $\mathcal{C}_1^e, \mathcal{C}_2^e, \mathcal{C}_1, \ldots, \mathcal{C}_{\tilde{K}}$

Simulation Results

- Test conditions:
  - JEM-7.0 with QP points: 27, 32, 37, 42
  - Random Access Main 10 (RA)
- 5 Classifiers for MCALF:
  - $D_P(K = 27)$
  - Product of D_R and $D_P(K = 27)$
  - $D_L\ (K = 25)$
  - D_P for $\mathcal{C}_1^e, \mathcal{C}_2^e\ (p = 0.63, K = 20)$ and $D_L\,(\tilde{K} = 25)$
  - D_R for $\mathcal{C}_1^e, \mathcal{C}_2^e\ (p = 0.63, K = 9)$ and $D_L\,(\tilde{K} = 25)$

Test Sequence	BD Rate (Y) RA
BQTerrace 1920 x 1080	**-1.34%**
MarketPlace 1920 x 1080	**-0.90%**
Rollercoaster 3840 x 2160	**-2.33%**
Encoder run-time	**107%**
Decoder run-time	**100%**

Coding gains of MCALF (5 classifiers) with reference GALF (1 classifier D_L)

Conclusion

- Performance of adaptive loop filter highly depends on classification
- Multiple classifications can better adapt to local features in video sequence
- Classification is performed through feature descriptors such as D_L, D_P or D_R and classification with confidence level
- We can get more than **2%** coding gain on top of GALF with **no increase of decoder runtime** and only small increase of encoder runtime

Thank you!

More Results

Test Sequence	BD Rate (Y) RA
BQTerrace 1920 x 1080	**-5.85%**
MarketPlace 1920 x 1080	**-3.35%**
Rollercoaster 3840 x 2160	**-6.31%**

Coding gains of MCALF (5 classifiers) with reference JEM-7.0 - GALF