

INTERFRAME-DEPENDENT RATE-QP-DISTORTION MODEL FOR VIDEO CODING AND TRANSMISSION

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Context - Motivation

Rate control is crucial to meet strict rate constraints in Ultra-low latency live streaming.



remote surgery



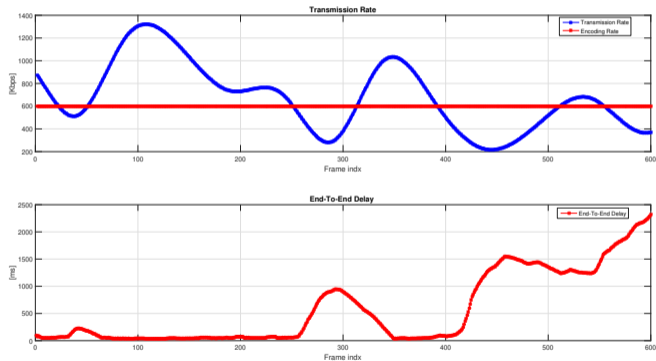
remote driving



sport events

Context - Motivation

Evolution of the end-to-end delay for video sequence encoding in 600kbps.



The mismatch between the encoding rate and available bandwidth may lead to an increase of the delay.

Context - Motivation

Excellent match between encoding rate and transmission rates requires
a frame-level model of encoding rate as a function of the quantization parameter.

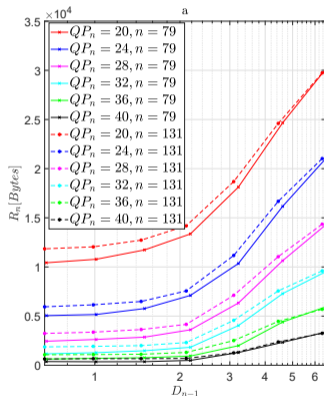
We propose a new model of the relation between R_n and QP_n depending on the Mean Square Error (MSE) distortion D_{n-1} for the reference frame n .

Inter-Dependent R-(QP,D) Model

For frame n , R_n depends on QP_n and D_{n-1} .

For a given QP_n , R_n increases :

- slowly when D_{n-1} is small,
- fast when D_{n-1} is large.



R_n for the frames $n = 79$ and 131 of *ParkScene* as a function of D_{n-1} for different values of QP_n .

Inter-Dependent R-(QP,D) Model

We propose the following R-(QP,D) model:

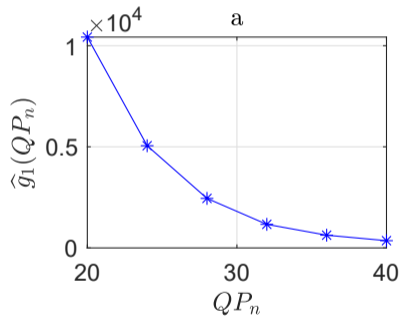
$$R_n(QP_n, D_{n-1}) = g_1(QP_n) + g_2(QP_n) (\tanh(g_3(QP_n) \log(D_{n-1}) - g_4(QP_n)) + 1), \quad (1)$$

where,

- $R_n(QP_n, D_{n-1}) = g_1(QP_n)$ when D_{n-1} is very small.
- $R_n(QP_n, D_{n-1}) = g_2(QP_n) (\tanh(g_3(QP_n) \log(D_{n-1}) - g_4(QP_n)) + 1)$ when D_{n-1} is very large.

Inter-Dependent R-(QP,D) Model.

$$g_1(QP_n) = p_1 \exp(-p_2 QP_n)$$

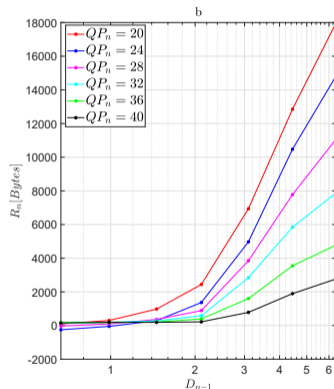


g_1 as a function of QP_n for frame 79 of ParkScene.

Inter-Dependent R-(QP,D) Model.

$$\begin{aligned} R_n^0(QP_n, D_{n-1}) &= R_n(QP_n, D_{n-1}) - g_1(QP_n) \\ &= g_2(QP_n) (\tanh(g_3(QP_n) \log(D_{n-1}) - g_4(QP_n)) + 1) \end{aligned}$$

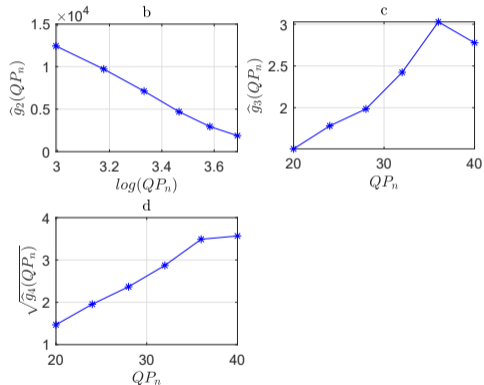
A least-squares estimation of g_2 , g_3 , and g_4 is performed using R_n^0 .



R_n^0 for frame $n = 79$ of *ParkScene* as a function of D_{n-1} for different values of QP_n .

Inter-Dependent R-(QP,D) Model.

- $g_2(QP_n) = p_3(-p_4 \log(QP_n) + 1)$
- $g_3(QP_n) = p_5 QP_n$
- $g_4(QP_n) = (p_6 QP_n - p_7)^2$



\hat{g}_2 , \hat{g}_3 , and \hat{g}_4 as a function of QP_n or $\log(QP_n)$ for frame 79 of ParkScene

Inter-Dependent R-(QP,D) Model.

In summary :

$$R_n(QP_n, D_{n-1}) = g_1(QP_n) + g_2(QP_n) (\tanh(g_3(QP_n) \log(D_{n-1}) - g_4(QP_n)) + 1) \quad (9)$$

with,

$$g_1(QP_n) = p_1 \exp(-p_2 QP_n)$$

$$g_2(QP_n) = p_3(-p_4 \log(QP_n) + 1)$$

$$g_3(QP_n) = p_5 QP_n$$

$$g_4(QP_n) = (p_6 QP_n - p_7)^2$$

Performance Evaluation

The proposed model is compared to models (1) , (2) and (3), **used at a frame level.**

Choi et al.¹:

$$R_k = M \cdot N \cdot MAD_k \cdot \left(\frac{p_1}{Q_k^2} + \frac{p_2}{Q_k} \right) \quad (1)$$

Ma et al.², Li et al.³:

$$R_k = p_1 \frac{SAD_k}{Q_k} + p_2 \quad (2)$$

Yang et al.⁴:

$$R_k = p_1 \cdot M \cdot N \frac{\sigma_k^2}{Q_k^2} \quad (3)$$

¹H. Choi, J. Yoo, J. Nam, *et al.*, "Pixel-wise unified rate-quantization model for multi-level rate control," *IEEE Journal in Signal Processing*, 2013.

²S. Ma, W. Gao, and Y. Lu, "Rate-distortion analysis for H.264/AVC video coding and its application to rate control," *IEEE transactions on circuits and systems*, 2005.

³Y. Li, H. Jia, P. Ma, *et al.*, "Inter-dependent rate-distortion modeling for video coding and its application to rate control," *IEEE*, 2014.

⁴X. Yang, Y. Tan, and N. Ling, "Rate control for H.264 with two-step quantization parameter determination but single-pass encoding," *EURASIP Journal*, 2006.

Experimental Setup

- Tested sequences: Tango, Racehorses, ParkScene and Magnycours.
- Encoder: x265 software⁵.
- Low delay configuration + Intra-refresh (cycle of one second).

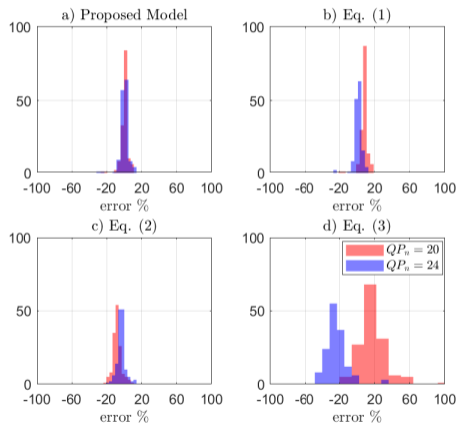
⁵MulticoreWare, *X265 software documentation*, <https://x265.readthedocs.io/en/master/>, 2020.

Experiment 1: Coding at constant QP

Performance at high bitrates coding

The proposed model provides the best performance at high bitrates:

- In fig (a), Model (9) errors: -13.6% to 14%,
- In fig (b) and (c), Models (1) and (2) errors: -11% to 19%,
- In fig (d), Model (3) errors: -50% to 64%.

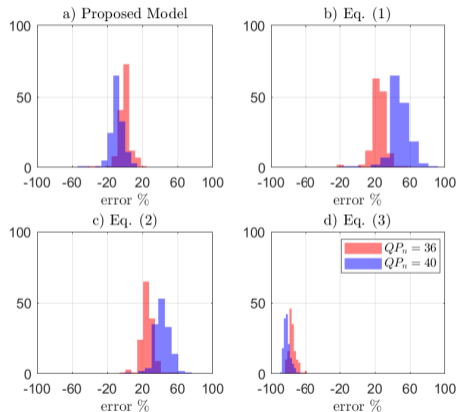


Histogram of prediction errors for *Tango* at high bitrates.

Performance at low bitrates coding

The proposed model significantly outperforms the three other models :

- In fig (a), (9) errors : -28.6% to 18.3%,
- In fig (b) and (c), Model (1) and (2) errors : 0% to 81% ,
- In fig (d), Model (3) errors : -90% to -58%.



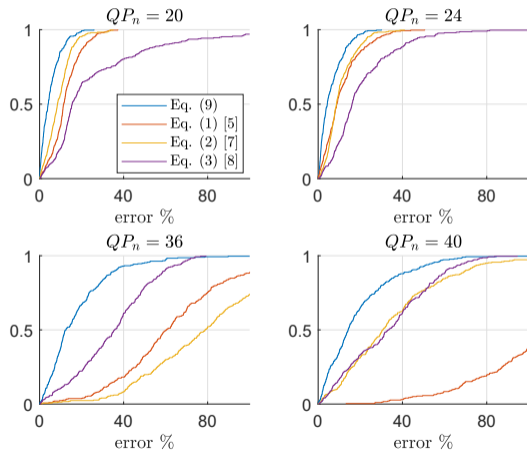
Histogram of prediction errors for *Tango* at low bitrates.

CDF of prediction errors - *Magnycours*

The proposed model achieves the lowest prediction error.

With $QP_n = 20$: 90% of the prediction errors are less than:

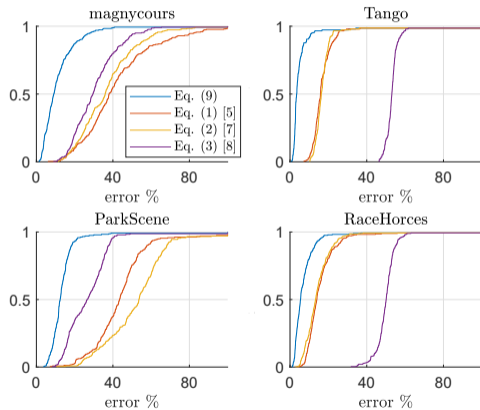
- 12.2% in Model (9).
- 16.7% and 22.6% in Model (1) and (2) respectively
- 51.8% in Model (3).



CDF of prediction errors for *Magnycours* sequence.

Average error CDF with constant QP

The proposed model achieves the best performance for all test sequences.

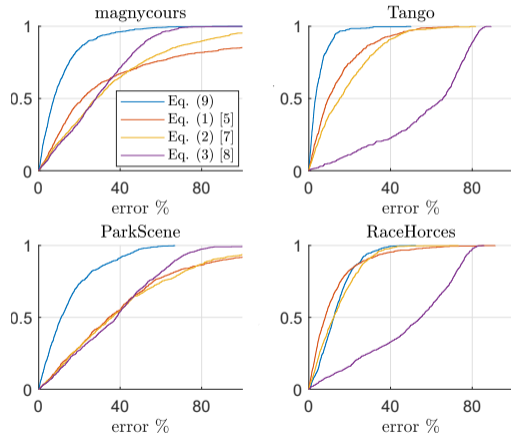


Average error CDF with constant QP for each sequence.

Experiment 2: Coding at time-varying QPs

Performance with time-varying QPs

The proposed model outperforms the other ones for all sequences.



Error CDF with first-order Markov process variations of QP for each sequences.

Conclusion

- **Contribution** : A new model of the relation between R_n and QP_n depending on D_{n-1} .
- The proposed model outperforms the other models in both constant QP coding and variable QP coding.
- The gains with our model tend to be more significant at low bitrates.
- **Future work** : Integration of the proposed model in a rate control algorithm for Ultra low-latency video streaming.

Questions ?

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