Transform Domain Temporal Prediction (TDTP)

- Traditional inter prediction copies pixels one-by-one.
- Suboptimal because it ignores spatial correlation.
- Transform Domain Temporal Prediction (TDTP): DCT (largely) achieves spatial decorrelation, enabling optimal one-to-one prediction.

Hidden Temporal Correlation at High Frequency

- Sub-Pixel Motion Compensation Interferes with TDTP
- Hidden Temporal Correlation at High Frequency
- Pixel-Domain Inter Prediction is Suboptimal

Transform Domain Temporal Prediction (TDTP): DCT (largely) achieves spatial decorrelation, inspiring the traditional pixel copying prediction. Thus we apply TDTP conditioned on the sub-pixel location.

As we operate this predictor in closed loop, the new reconstructed frames (which are prediction reference for future frames) have different statistics, for which the correlation coefficient $\rho \neq \rho'$. This deviation in statistics between design and operation grows over frames. Thus we propose the asymptotic closed-loop (ACL) design approach for TDTP.

ACL is an iterative open-loop design technique that asymptotically optimizes the system for closed-loop operation.

As we operate this predictor in closed loop, the new reconstructed frames (which are prediction reference for future frames) have different statistics, for which the correlation coefficient $\rho \neq \rho'$. This deviation in statistics between design and operation grows over frames. Thus we propose the asymptotic closed-loop (ACL) design approach for TDTP.

ACL is an iterative open-loop design technique that asymptotically optimizes the system for closed-loop operation.

Given the reconstructed data at iteration $t - 1$, $\hat{x}_{n-1,t-1}$ ($n = 2\ldotsN$), estimate the prediction coefficient for iteration $t$, $\rho_t = E(\hat{x}_{n,t}/E(\hat{x}_{n-1,t-1}))$.

Then employ open-loop prediction to generate, $\hat{x}_{n,t} = \rho_t \hat{x}_{n-1,t-1}$.

Since $\rho_t$ is directly optimized for the statistics of $\hat{x}_{n-1,t-1}$ ($n = 2\ldotsN$), the prediction $\hat{x}_{n,t}$ is guaranteed to improve.

Better prediction usually leads to better reconstruction, $\hat{x}_{n,t}$, and vice versa.

The reconstruction error decreases over iterations and on convergence, $\hat{x}_{n,t} = \hat{x}^*_n$, which is equivalent to the closed-loop system.

Instability due to Quantization Error Propagation

As we operate this predictor in closed loop, the new reconstructed frames (which are prediction reference for future frames) have different statistics, for which the correlation coefficient $\rho \neq \rho'$. This deviation in statistics between design and operation grows over frames. Thus we propose the asymptotic closed-loop (ACL) design approach for TDTP.

As we operate this predictor in closed loop, the new reconstructed frames (which are prediction reference for future frames) have different statistics, for which the correlation coefficient $\rho \neq \rho'$. This deviation in statistics between design and operation grows over frames. Thus we propose the asymptotic closed-loop (ACL) design approach for TDTP.

Two Loop Asymptotic Closed-Loop (ACL) Design for TDTP

- In video coding, encoder decisions (e.g. mode decisions, motion vectors, quantization, etc.) are dependent on the prediction.
- Thus we proposed a two-loop design scheme: Inner loop: Estimate prediction coefficient $\rho$ via ACL with encoder decisions fixed. Outer loop: Update encoder decisions with $\rho$ fixed.
- We design different prediction coefficients conditioned on: sub-pixel location, quantization parameter (QP), skip/non-skip mode

Experimental Results

- The proposed approach was implemented in HM 14.0. Both prediction size and transform size are restricted to 8x8, and the motion search is at half-pixel precision.
- The average bitrate reduction over standard HEVC is 6.53% for training set (Exp1) and 4.96% outside training set (Exp2).
- In Exp2 we provide a choice of 8 sets of prediction coefficients at the encoder with an overhead of 3 bits per sequence. The difference between the two experiments suggests further scope for adaptivity.