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Distributed Video Coding with Particle Filtering for Correlation Tracking

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Problem







Related correlation modelling approaches

- Modelling correlation error as a Gaussian or Laplacian random variable with statistics estimated from previously decoded frames
- Vary the correlation noise statistics from pixel to pixel depending on the pixel difference between motion compensated blocks of 2 key frames providing side information
- Motion estimation with unsupervised learning where messages are iterated between the SW Decoder and the motion estimation block to generate better side-information/update probability model (Varodayan et al., 2008)

Contribution

- Current approaches adjust the correlation model online from previously decoded frames, providing updated statistics to the Slepian-Wolf decoder
 - However, once Slepian-Wolf (SW) decoding starts, correlation model is fixed
- We incorporate correlation estimation within our iterative SW decoder fitted with a particle filter (PF) to estimate correlation at bit level
 - Motivation: standard belief-propagation-based SW decoder cannot track varying correlation and cannot handle continuous variables like correlation

Adaptive SW decoding with PF

- SW decoder based on belief-propagation (BP) decoding of LDPC code factor graph
- Add to the LDPC factor graph with N source nodes x and M syndromes: N' correlation variable nodes p and N correlation factor nodes f_i, where

$$f_i(x_i) = \begin{cases} 1-p, & \text{if } x_i = y_i \\ p, & \text{otherwise} \end{cases}$$

Factor graph construction



Non-stationarity of *p* over time

- Connect *p* nodes to correlation factor nodes, which in turn are connected to source variable nodes *x* to check if *x*=*y*
- Number of correlation factor nodes connected to each variable node *p* is termed connection ratio

Factor graph construction



Non-stationarity of *p* over time

• Insert additional factor nodes $f_{i,j}$ connecting adjacent p nodes

$$f_{i,j}(p_i, p_j) = \frac{1}{\sqrt{2\pi\lambda}} \exp\left(-\frac{(p_j - p_i)^2}{2\lambda}\right)$$

SW decoder graph with PF



Message passing algorithm

Initialize the values of message and particles



True, or maximum number of iterations reached

Export the decoded codeword

Particle filtering in Region 1





Parameters

- Tuneable parameters:
 - X and Y quantization ratio \rightarrow Q=3, 4, 5 bits/pixel
 - hyper-prior $\lambda \rightarrow 0.1$
 - connection ratio between regions 1 and 2 \rightarrow 16
 - Metropolis-Hastings random walk → enabled
 - maximum number of iterations \rightarrow 100
 - number of particles \rightarrow 10
 - initial estimate of correlation $p \rightarrow 0.13$
- 16 frames of Coast and Car sequences
- Assume that key frames available at the decoder are perfectly reconstructed
- Rate=number of syndrome bits/number of quantized bits

Results: Car video sequence



Results: Car video sequence



Results: Reconstruction of Frame 7 with Q=3





Without BPPF correlation tracking

With proposed system

Results: Coast video sequence



Results: Coast video sequence



Conclusions

- Performance improvement of DVC by incorporating correlation estimation via PF within the SW BP decoder
- ✓ Our PF-based BP helps estimate correlation evolving over time, improving SW decoder performance
- Developed a tool with a number of tuneable parameters, which can be optimised
- ✓ Our set-up can be used with DCT-based DVC, with/without feedback, and even with correlation noise modelling outside SW decoder

Further work

- SW BPPF decoding with bit-plane splitting
- Modelling correlation noise as AWGN or Laplacian
- > Optimise tunable parameters
- Use correlation estimation approaches prior to SW decoding to initialise parameters