Neural Distributed Image Compression Using Common Information

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1 Equal contribution.

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System Model: Point-to-point

Source coding

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Source coding

- Lossless

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- Lossy

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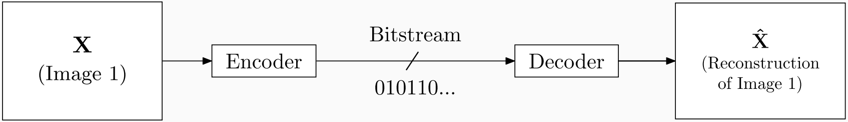

System model for point-to-point source coding.

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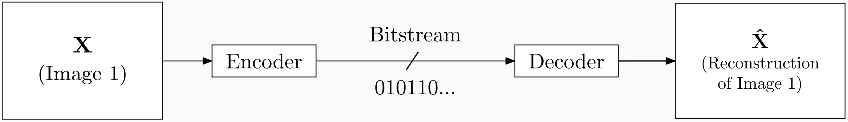

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Two competing goals in lossy compression:

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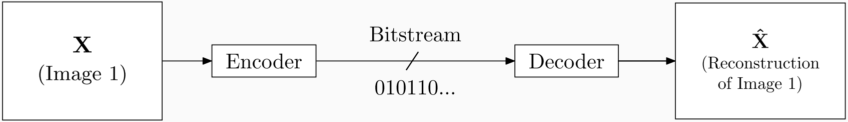

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Two competing goals in lossy compression:

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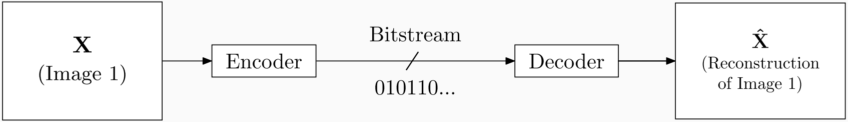

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- Rate
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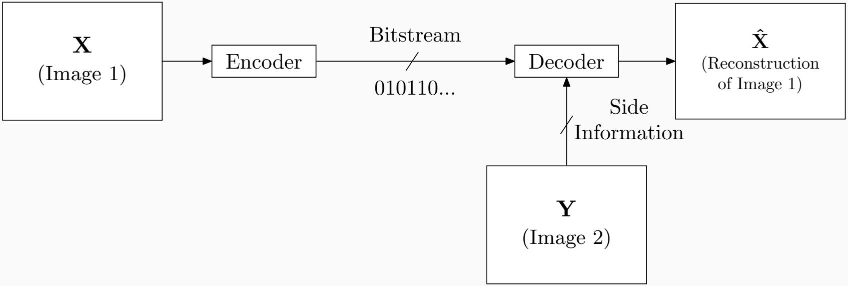

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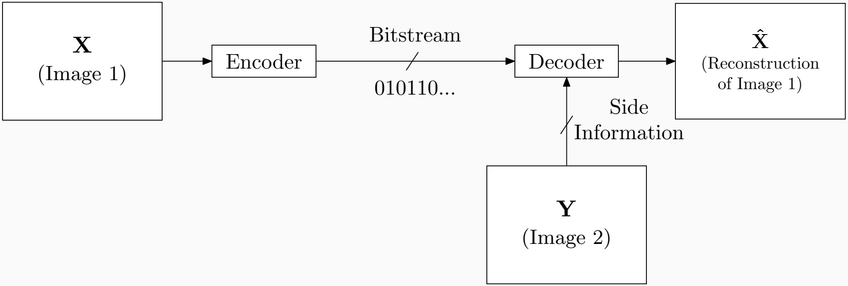

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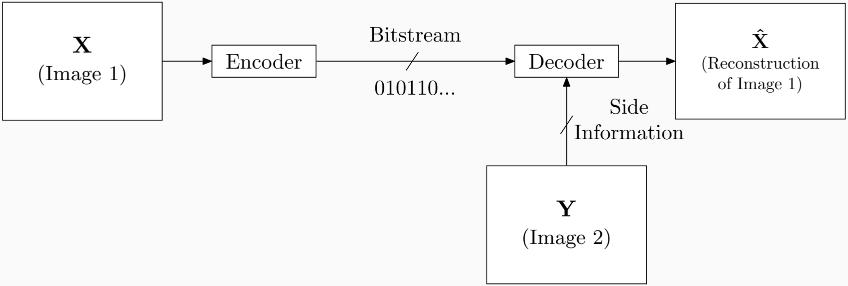

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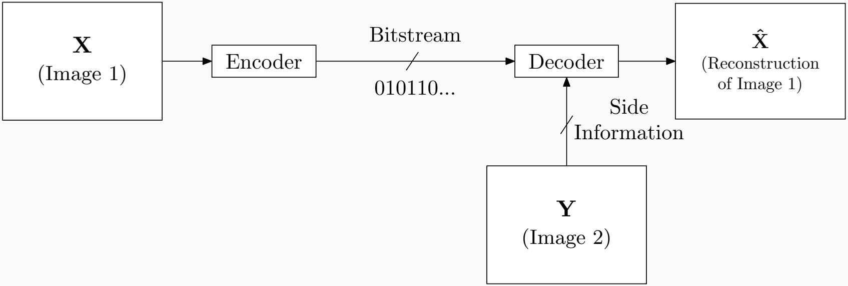

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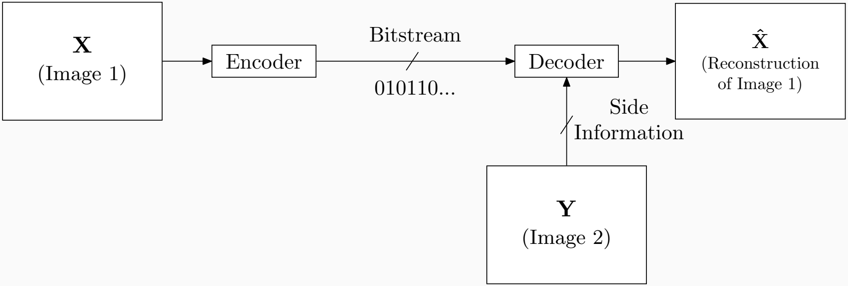

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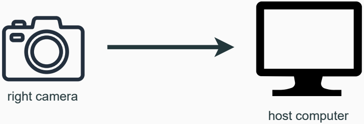

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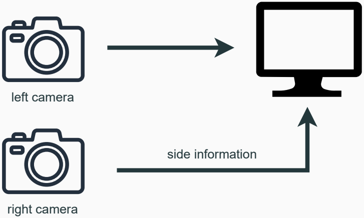
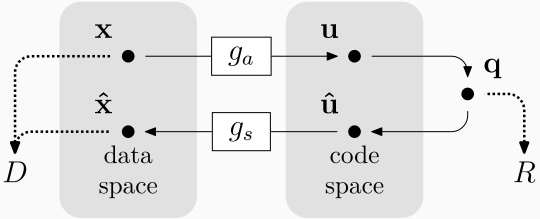
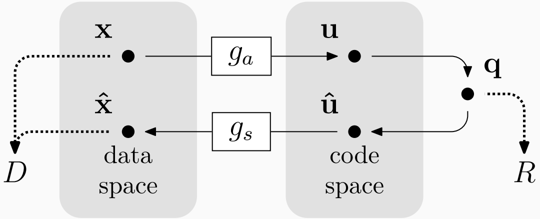


Lossy Compression: Transform Coding



Transform coding framework[1].

[1] Figure provided is from Ballé et al., 2017.



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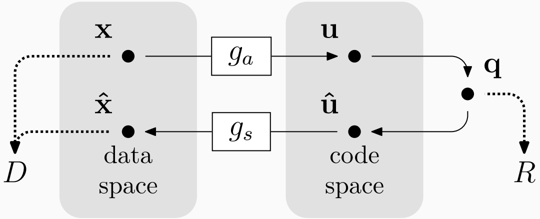

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$$L(\mathbf{g}_a, \mathbf{g}_s) = R + \lambda D,$$

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$$R = \mathbb{E}_{\mathbf{x} \sim p(\mathbf{x})} [\underbrace{-\log p(\tilde{\mathbf{u}} \mid \tilde{\mathbf{z}})}_{\text{latent}}] + \mathbb{E}_{\mathbf{x} \sim p(\mathbf{x})} [\underbrace{-\log p(\tilde{\mathbf{z}})}_{\text{hyperprior}}]$$

Deep Image Compression with Side Information

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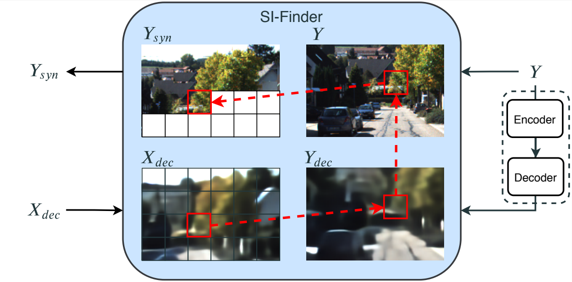

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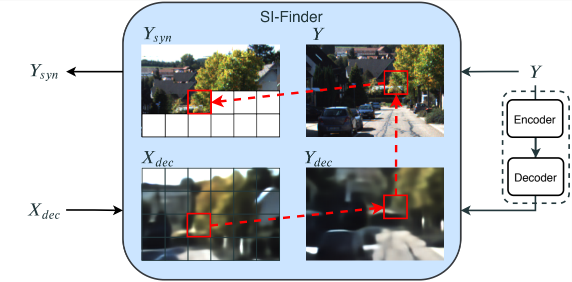
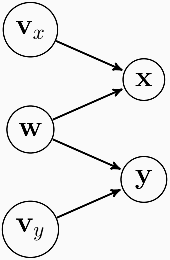


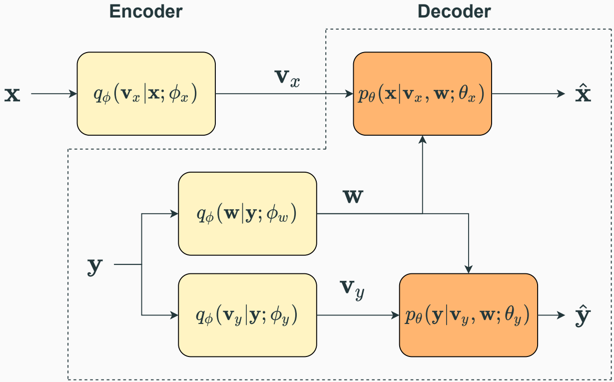
- Whang et. al., 2021 - Transform side information image to a latent space. Use it together with the received latent variable to jointly reconstruct the image.

Proposed Solution

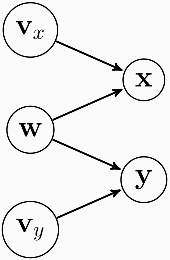
Distributed Source Coding Architecture



Graphical model. [Wang et al., 2017]



Distributed source coding architecture.



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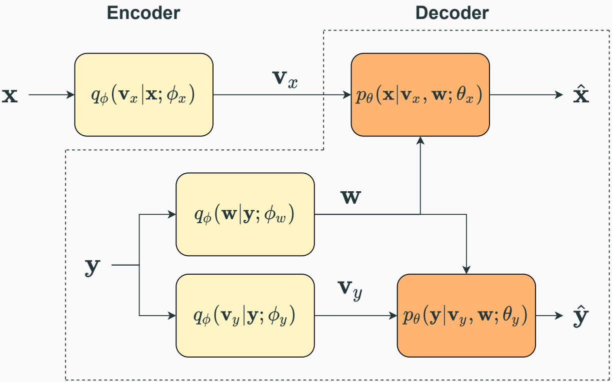
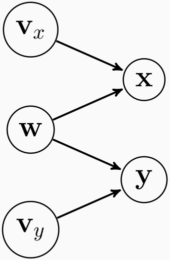


Distributed source coding architecture.

$\mathbf{v}_x$, $\mathbf{v}_y$ and $\mathbf{w}$ are independent latent variables:

- $\mathbf{w}$ - common information.
- $\mathbf{v}_x$ and $\mathbf{v}_y$ - independent information of $\mathbf{x}$ and $\mathbf{y}$.
- Generate $\mathbf{x}$ and $\mathbf{y}$ as above.

Distributed Source Coding Architecture



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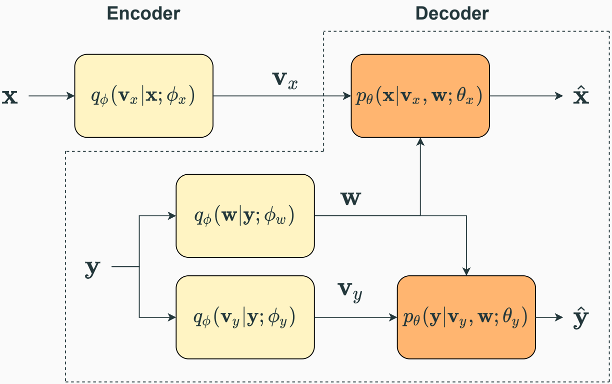
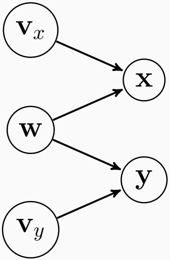


Distributed source coding architecture.

$$p(\mathrm{x}, \mathrm{y}, \mathrm{w}, \mathrm{v}_x, \mathrm{v}_y) = p(\mathrm{w})p(\mathrm{v}_x)p(\mathrm{v}_y)p_{\boldsymbol{\theta}}(\mathrm{x} \mid \mathrm{w}, \mathrm{v}_x; \boldsymbol{\theta}_x)p_{\boldsymbol{\theta}}(\mathrm{y} \mid \mathrm{w}, \mathrm{v}_y; \boldsymbol{\theta}_y)$$

Factored joint prior distribution of the latent variables emerging from the graphical model.

Distributed Source Coding Architecture



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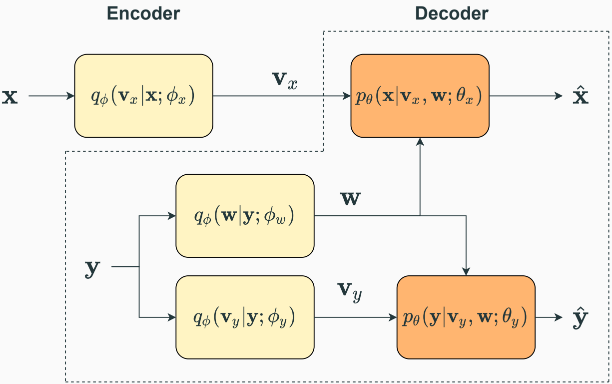

Distributed source coding architecture.

$$q_\phi(\mathrm{w}, \mathrm{v}_x, \mathrm{v}_y \mid \mathrm{x}, \mathrm{y}) = q_\phi(\mathrm{v}_x \mid \mathrm{x}; \phi_x) q_\phi(\mathrm{w} \mid \mathrm{y}; \phi_w) q_\phi(\mathrm{v}_y \mid \mathrm{y}; \phi_y)$$

Factored variational approximation of the posterior distribution emerging from the system architecture.

Loss Function

$$\min_{\boldsymbol{\phi},\boldsymbol{\theta}} \mathbb{E}_{\mathsf{x},\mathsf{y}\sim p(\mathsf{x},\mathsf{y})} D_{\mathrm{KL}}\left[q_{\boldsymbol{\phi}}(\tilde{\mathsf{v}}_x, \mathsf{v}_y, \mathsf{w} \mid \mathsf{x}, \mathsf{y}) \mid\mid p(\tilde{\mathsf{v}}_x, \mathsf{v}_y, \mathsf{w} \mid \mathsf{x}, \mathsf{y})\right]$$

Loss Function

$$
\begin{aligned}
&\min_{\boldsymbol{\phi},\boldsymbol{\theta}} \mathbb{E}_{\mathrm{x},\mathrm{y}\sim p(\mathrm{x},\mathrm{y})} D_{\mathrm{KL}} \left[q_{\boldsymbol{\phi}}(\tilde{\mathrm{v}}_x, \mathrm{v}_y, \mathrm{w} \mid \mathrm{x}, \mathrm{y}) \,||\, p(\tilde{\mathrm{v}}_x, \mathrm{v}_y, \mathrm{w} \mid \mathrm{x}, \mathrm{y}) \right] \\
&= \min_{\boldsymbol{\phi},\boldsymbol{\theta}} \mathbb{E}_{\mathrm{x},\mathrm{y}\sim p(\mathrm{x},\mathrm{y})} \mathbb{E}_{\tilde{\mathrm{v}}_x,\mathrm{v}_y,\mathrm{w}\sim q_{\boldsymbol{\phi}}} \Bigg(\Big(\log q_{\boldsymbol{\phi}}(\tilde{\mathrm{v}}_x \mid \mathrm{x}; \boldsymbol{\phi}_x) + \log q_{\boldsymbol{\phi}}(\mathrm{v}_y \mid \mathrm{y}; \boldsymbol{\phi}_y) + \log q_{\boldsymbol{\phi}}(\mathrm{w} \mid \mathrm{y}; \boldsymbol{\phi}_f) \Big) \\
&\qquad - \Big(\underbrace{\log p_{\boldsymbol{\theta}}(\mathrm{x} \mid \mathrm{w}, \tilde{\mathrm{v}}_x; \boldsymbol{\theta}_x)}_{D_x} + \underbrace{\log p_{\boldsymbol{\theta}}(\mathrm{y} \mid \mathrm{w}, \mathrm{v}_y; \boldsymbol{\theta}_y)}_{D_y} + \underbrace{\log p(\mathrm{w})}_{R_w} + \underbrace{\log p(\tilde{\mathrm{v}}_x)}_{R_x} + \underbrace{\log p(\mathrm{v}_y)}_{R_y} \Big) \Bigg) \\
&\qquad + \mathit{const.}
\end{aligned}
$$

Loss Function

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$$= \min_{\boldsymbol{\phi},\boldsymbol{\theta}} \mathbb{E}_{\mathrm{x},\mathrm{y}\sim p(\mathrm{x},\mathrm{y})} \mathbb{E}_{\tilde{\mathrm{v}}_x, \mathrm{v}_y, \mathrm{w}\sim q_{\boldsymbol{\phi}}} \Bigg(\Big(\log q_{\boldsymbol{\phi}}(\tilde{\mathrm{v}}_x \mid \mathrm{x}; \boldsymbol{\phi}_x) + \log q_{\boldsymbol{\phi}}(\mathrm{v}_y \mid \mathrm{y}; \boldsymbol{\phi}_y) + \log q_{\boldsymbol{\phi}}(\mathrm{w} \mid \mathrm{y}; \boldsymbol{\phi}_f) \Big)$$

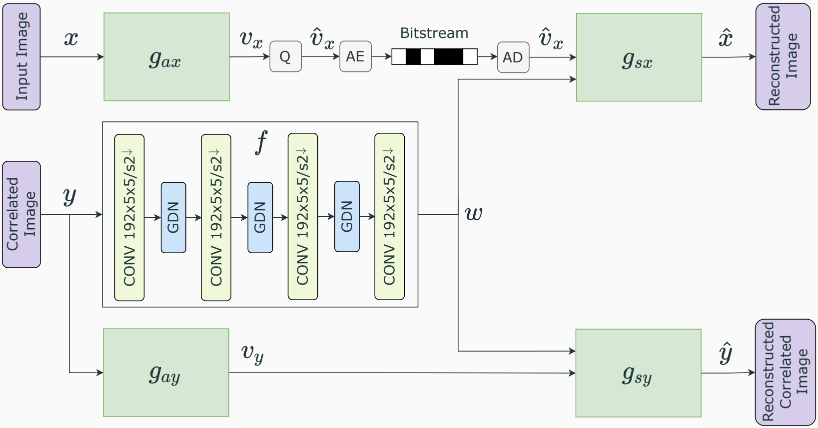
$$- \Big(\underbrace{\log p_{\boldsymbol{\theta}}(\mathrm{x} \mid \mathrm{w}, \tilde{\mathrm{v}}_x; \boldsymbol{\theta}_x)}_{D_x} + \underbrace{\log p_{\boldsymbol{\theta}}(\mathrm{y} \mid \mathrm{w}, \mathrm{v}_y; \boldsymbol{\theta}_y)}_{D_y} + \underbrace{\log p(\mathrm{w})}_{R_w} + \underbrace{\log p(\tilde{\mathrm{v}}_x)}_{R_x} + \underbrace{\log p(\mathrm{v}_y)}_{R_y} \Big) \Bigg)$$

$$+ \, const.$$

Adding weights α, β and λ to control the contribution of the terms, we write:

$$L(\mathrm{g}_{ax}, \mathrm{g}_{sx}, \mathrm{g}_{ay}, \mathrm{g}_{sy}, \mathrm{f}) = (R_x + \lambda D_x) + \alpha\,(R_y + \lambda D_y) + \beta R_w,$$

Neural Network Architecture



Experimental Setup and Results

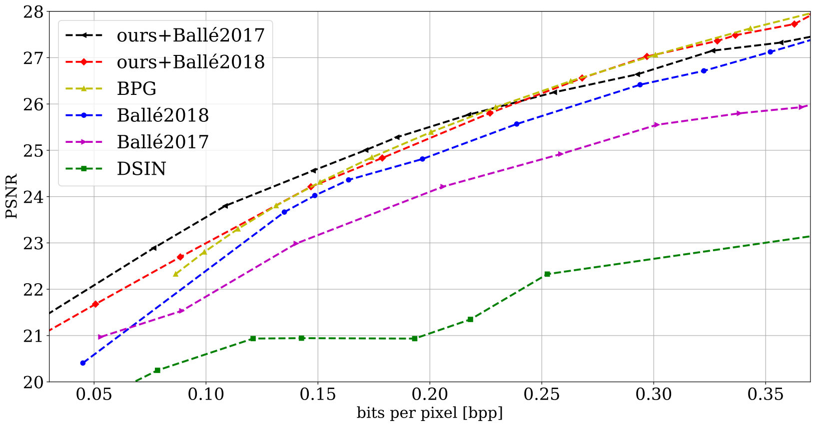
Datasets

KITTI Stereo

Cityscape

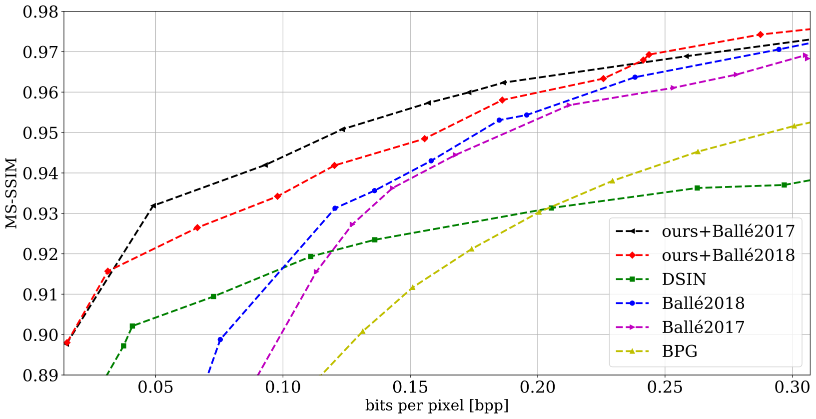
Example stereo image pairs from KITTI Stereo and Cityscape.

Results with KITTI Stereo



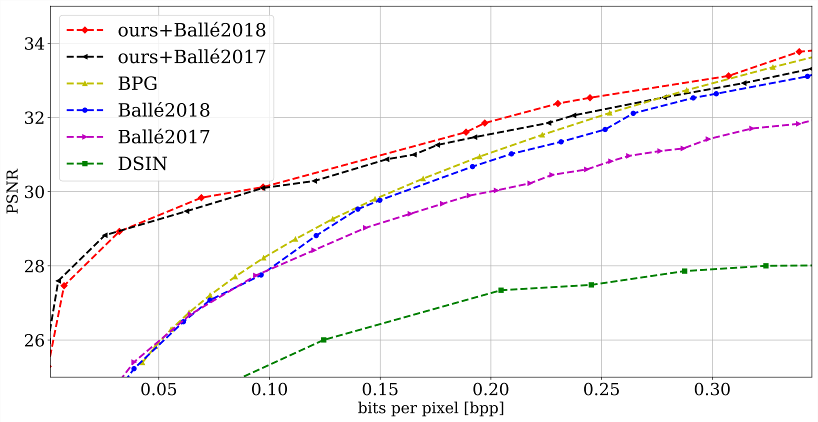
Comparison of different models in terms of PSNR.

Results with KITTI Stereo



Comparison of different models in terms of MS-SSIM.

Results with Cityscape dataset



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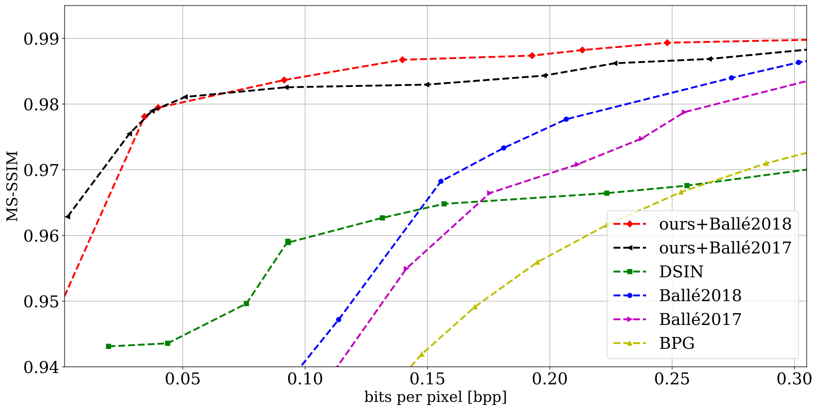

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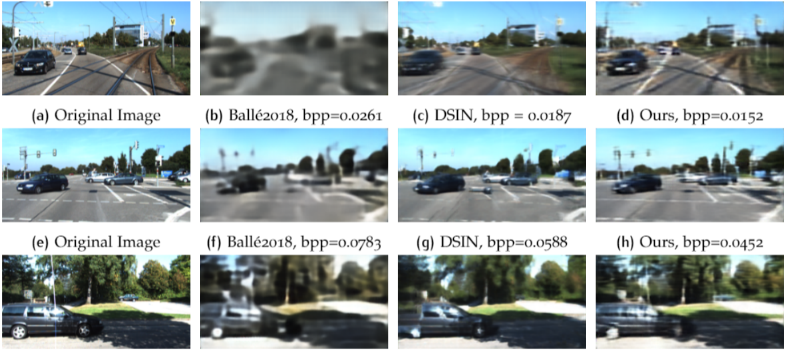
Visual Comparisons



(a) Original Image (b) Ballé2018, bpp=0.0261 (c) DSIN, bpp = 0.0187 (d) Ours, bpp=0.0152

(e) Original Image (f) Ballé2018, bpp=0.0783 (g) DSIN, bpp=0.0588 (h) Ours, bpp=0.0452

(i) Original Image (j) Ballé2018, bpp = 0.0827 (k) DSIN, bpp = 0.0741 (l) Ours, bpp = 0.0521

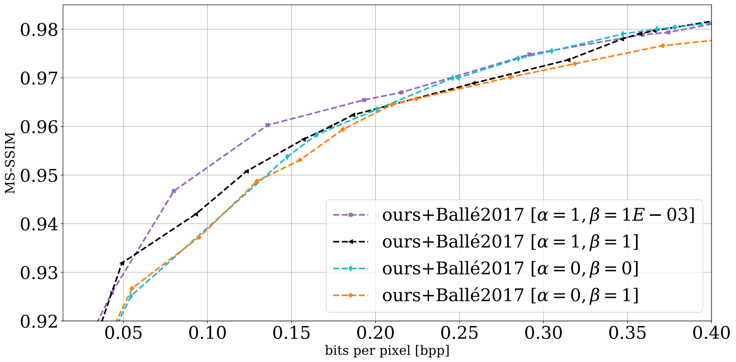
"Ours" refers to "Ours + Ballé2017" model.

Visual Comparisons

(a) DSIN, bpp=0.0449

(b) Ours, bpp=0.0431

Effect of hyperparameters α and β



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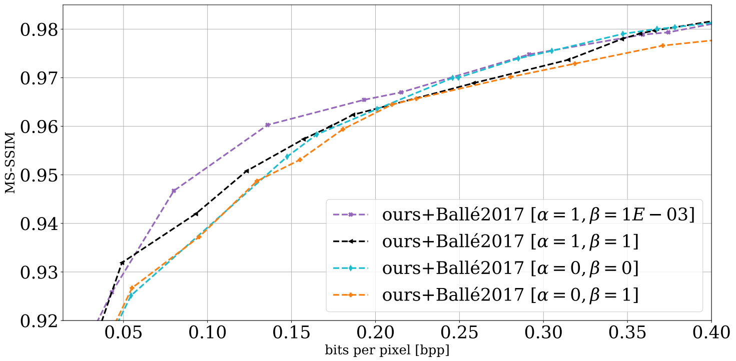

$$(R_x + \lambda D_x) + \alpha (R_y + \lambda D_y) + \beta R_w$$

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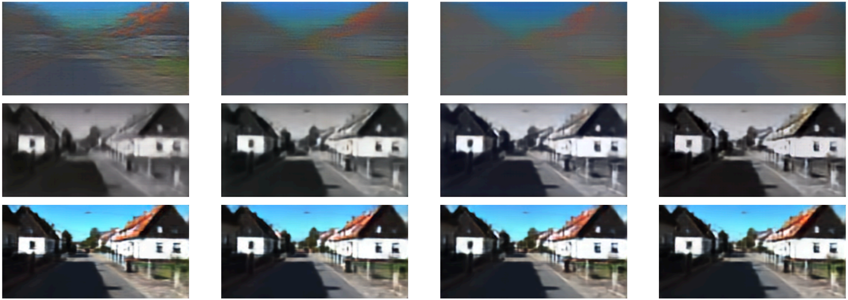

(a) $\alpha = 1, \beta = 10^{-3}$ bpp $= 0.1281$ (b) $\alpha = 0, \beta = 0$ bpp $= 0.1572$ (c) $\alpha = 1, \beta = 1$ bpp $= 0.1658$ (d) $\alpha = 0, \beta = 1$ bpp $= 0.1731$

Common information (1st row), private information (2nd row) decomposition, reconstructed images with similar reconstruction quality (3rd row).

Conclusion

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- Neural network learns side information statistics despite not having access to its realization.
- A novel approach by disentangling common and private information.
- Significant reductions in bit rates by only sending the private information to the decoder.
- Common information consists of global texture and color details, which can be controlled using hyperparameters.

Code publicly available at: *`https://github.com/ipc-lab/NDIC`*