An Efficient Compression Method for Sign Information of DCT Coefficients via Sign Retrieval

Chihiro Tsutake* Keita Takahashi Toshiaki Fujii

Nagoya University, Japan

Thank you for watching this video.

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We'd like to talk on "An Efficient Compression Method for Sign Information of DCT Coefficients via Sign Retrieval".

An Efficient Compression Method for Sign Information of DCT Coefficients via Sign Retrieval

Chihiro Tsutake*　　Keita Takahashi　　Toshiaki Fujii

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Today, we will give a new theory, how to improve an efficiency of an image compression technique based on the discrete cosine transformation (DCT).

Our achievement

First of all, we summarize our achievement.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)

We focus on the lossless compression of sign information of DCT coefficients.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)

It is unachievable in theory because signs are equiprobable.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)

So, the sign compression was a long-standing problem in image compression.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)
- DCT-based image compression + Phase Retrieval

We solved this problem by using classical image restoration technique, referred to as phase retrieval.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)
- DCT-based image compression + Phase Retrieval → Sign Retrieval

Because the phase retrieval will be applied to retrieve the sign information,
we named our sign compression theory as sign retrieval.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)
- DCT-based image compression + Phase Retrieval → Sign Retrieval
- The bit amount of the sign information was half of JPEG (twice better performance)

By using our theory, we achieved the half amount of sign bits compared with JPEG.

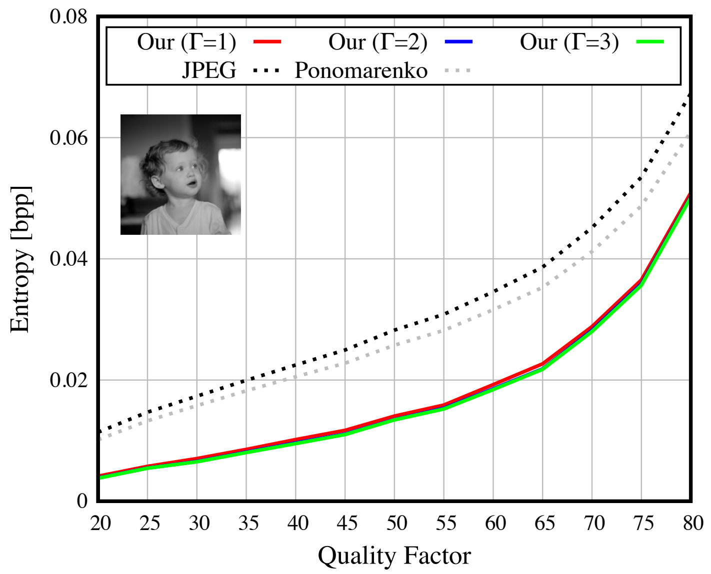
Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)
- DCT-based image compression + Phase Retrieval → Sign Retrieval
- The bit amount of the sign information was half of JPEG (twice better performance)

In other words, we achieved twice better compression performance than JPEG.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)
- DCT-based image compression + Phase Retrieval → Sign Retrieval
- The bit amount of the sign information was half of JPEG (twice better performance)



This figure shows an example of our rate curve,
where the horizontal and vertical axes represent the quality factor and the entropy of signs, respectively.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)
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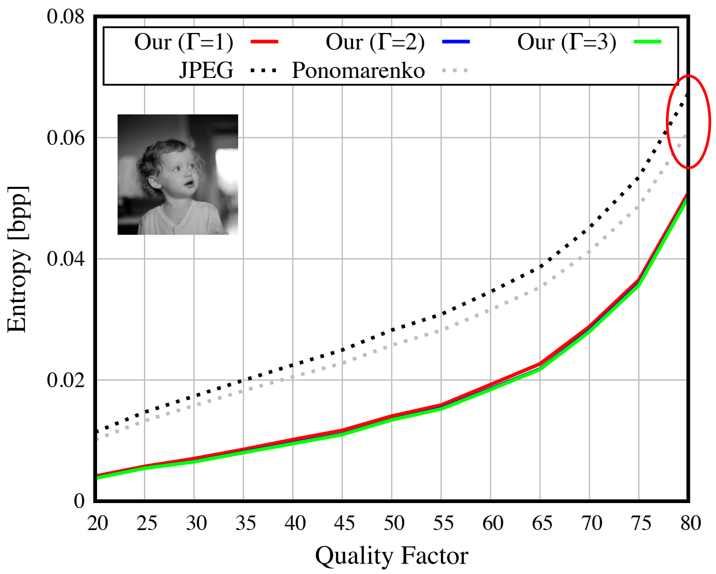
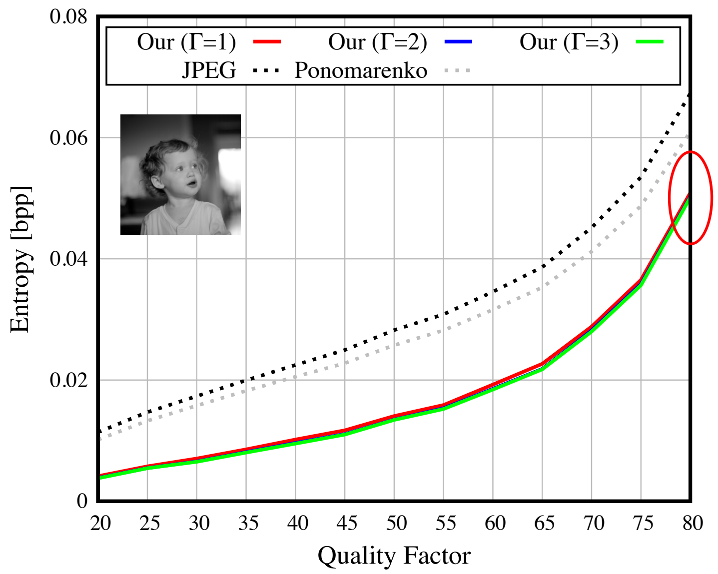


The dashed lines are JPEG and a previous sign compression technique.

Our achievement

- Lossless compression of sign information of DCT coefficients (incompressible in theory)
- DCT-based image compression + Phase Retrieval → Sign Retrieval
- The bit amount of the sign information was half of JPEG (twice better performance)



The solid lines are our results,
where we can confirm the twice better performance.

Agenda

The agenda is here.

Agenda

1. Introduction

2. Proposed Method
   2.1. Encoder and Decoder
   2.2. Sign Retrieval and Its Solution

3. Experimental Results

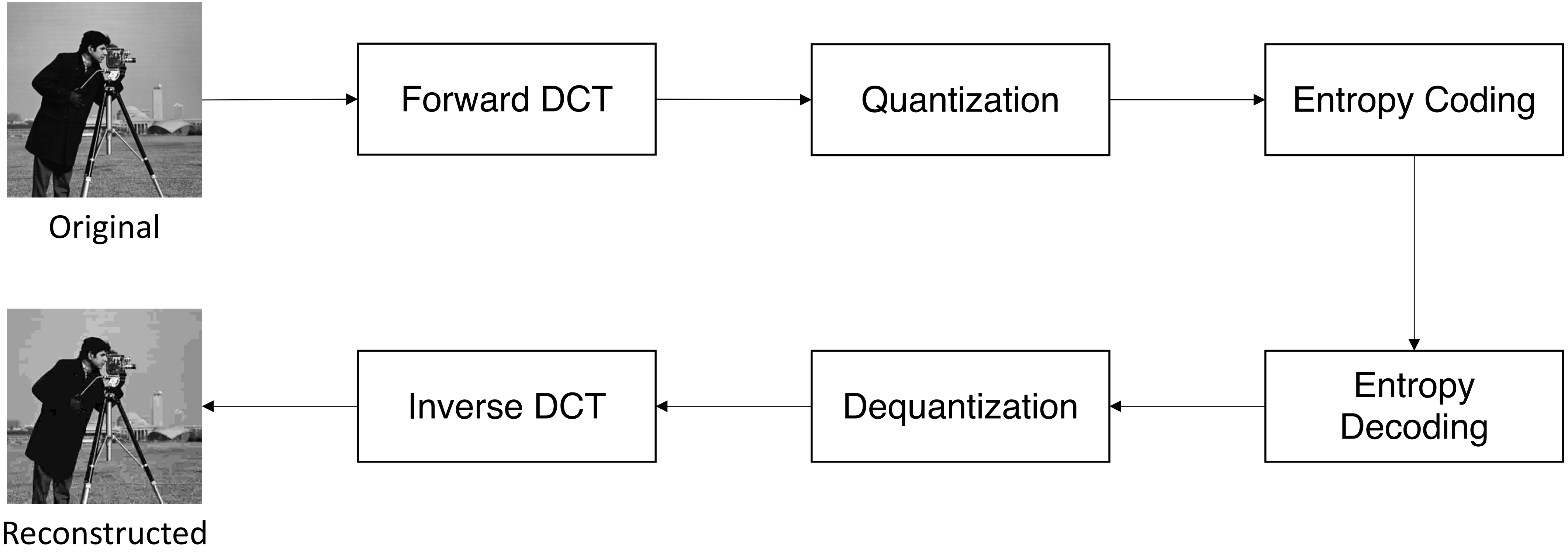
4. Conclusion

To elaborate our theory, we first introduce an overview of a DCT-based image compression technique.

Introduction

Image Compression based on Discrete Cosine Transformation (DCT)

- JPEG, MPEG, AVC, HEVC,…

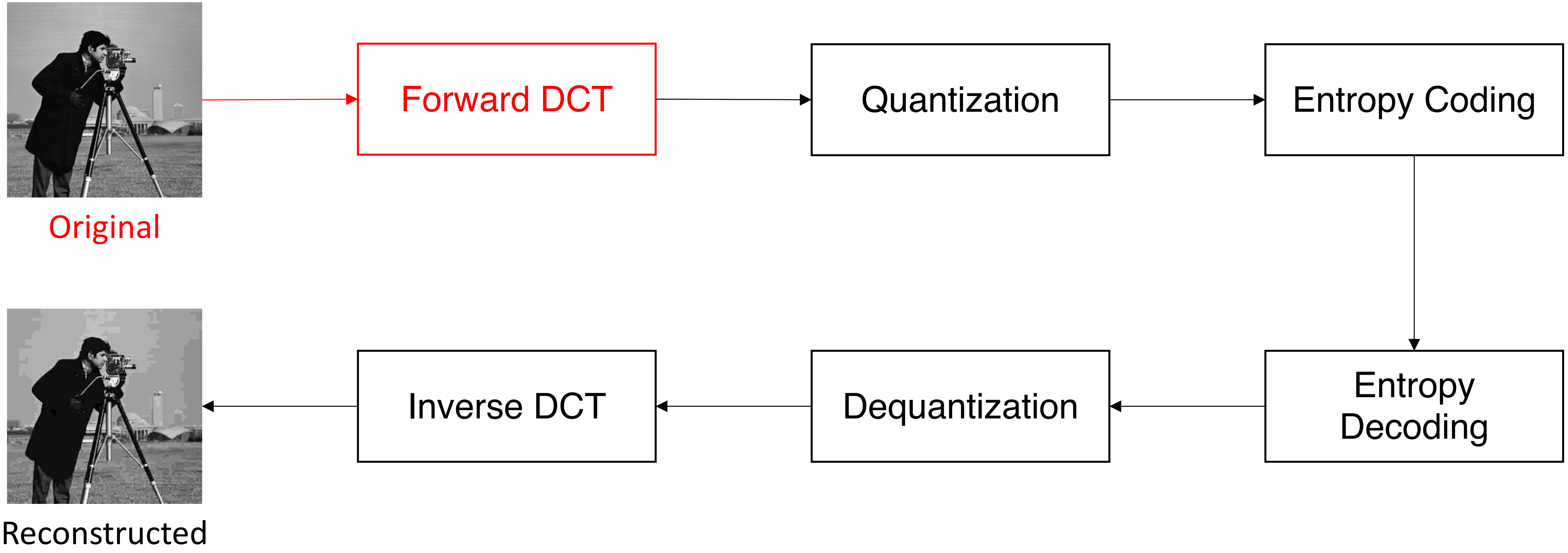


The DCT is known as a fundamental technology in image compression,
and it is applied to various image compression techniques such as JPEG, MPEG, and so on.

Introduction

Image Compression based on Discrete Cosine Transformation (DCT)

- JPEG, MPEG, AVC, HEVC,…

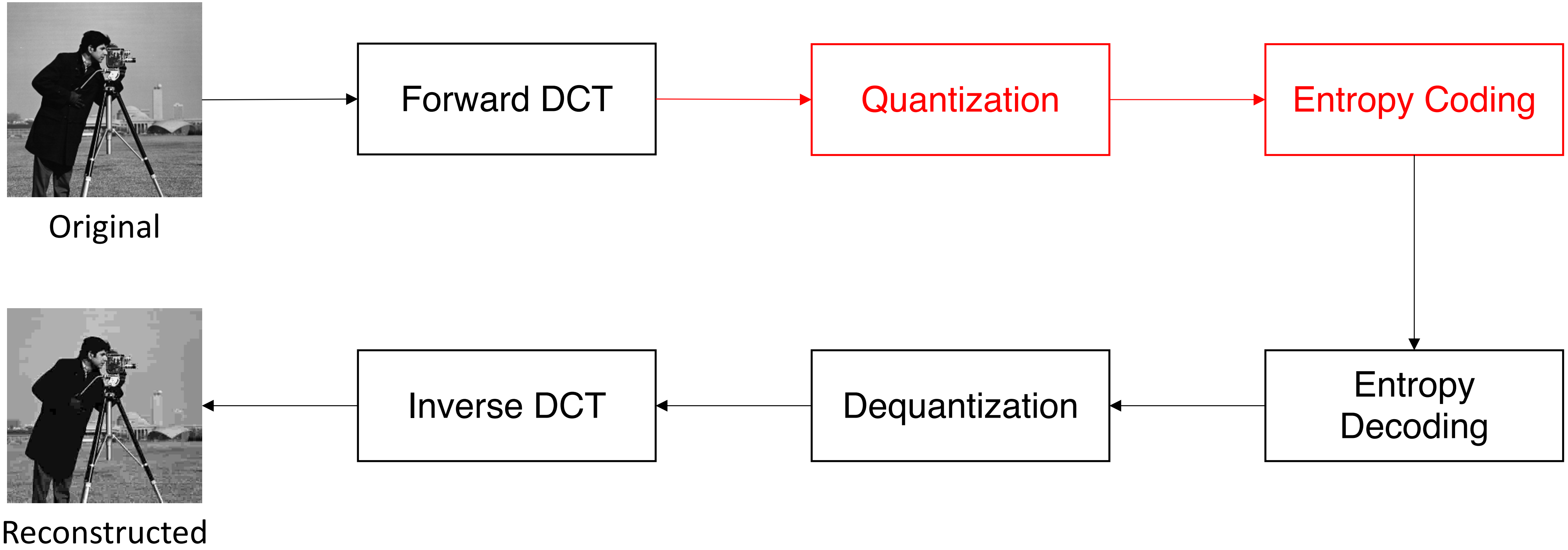


A typical DCT-based technique first transforms an original image into the cosine domain.

Introduction

Image Compression based on Discrete Cosine Transformation (DCT)

- JPEG, MPEG, AVC, HEVC,…

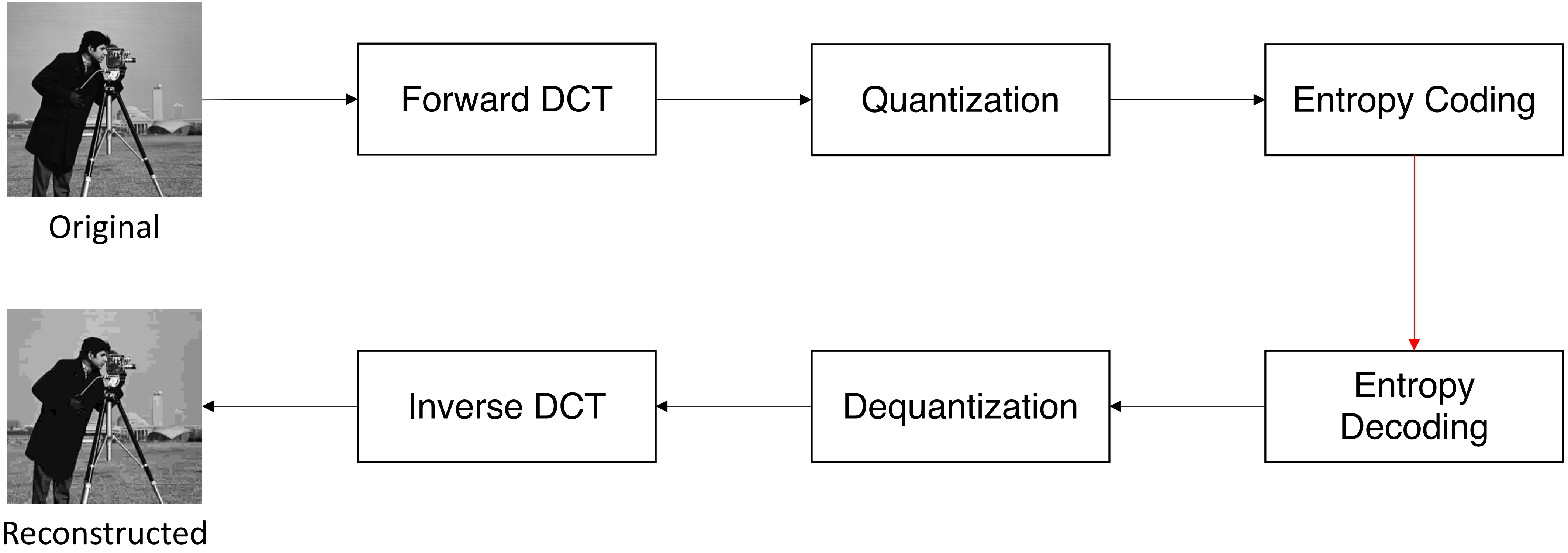


The quantization and entropy coding are then applied to DCT coefficients.

Introduction

Image Compression based on Discrete Cosine Transformation (DCT)

- JPEG, MPEG, AVC, HEVC,…

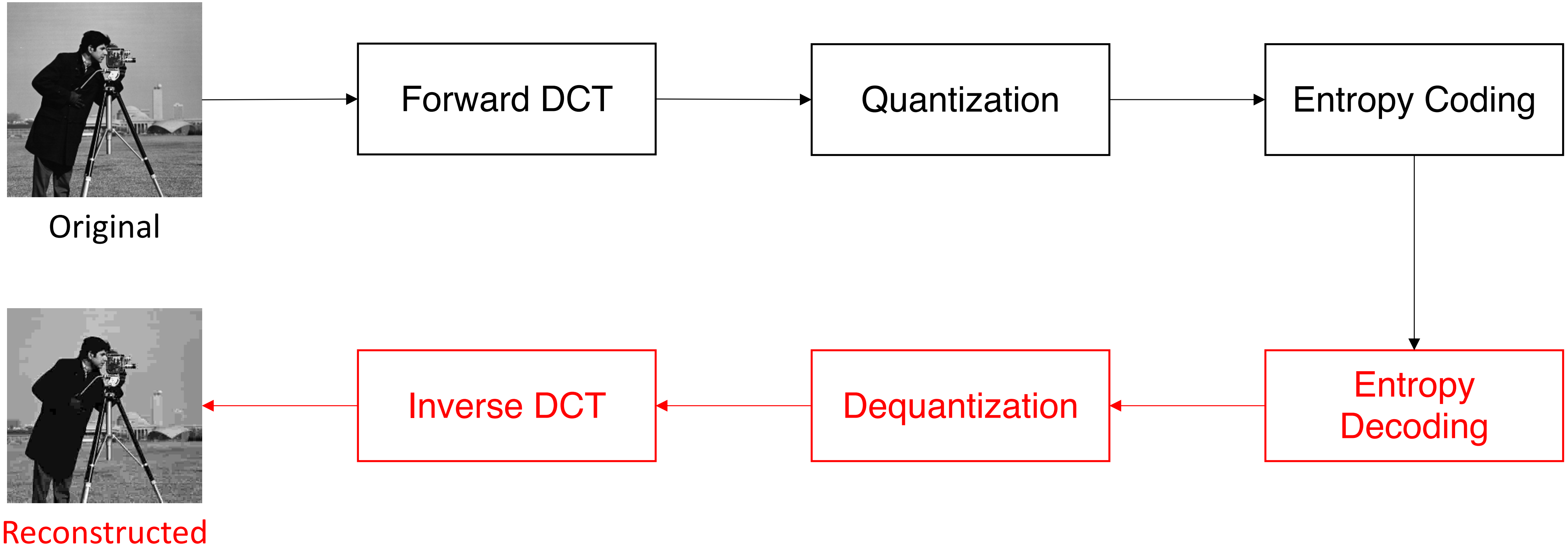


Finally, the resulting bitstream is transmitted to the decoder.

Introduction

Image Compression based on Discrete Cosine Transformation (DCT)

- JPEG, MPEG, AVC, HEVC,…



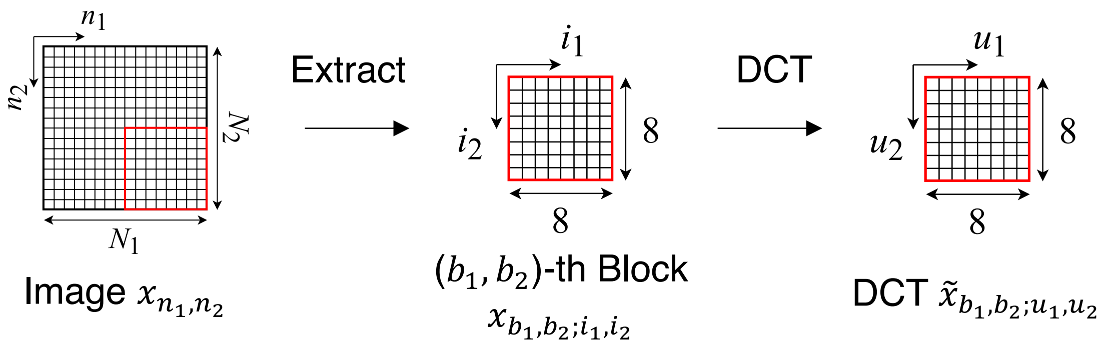
The decoder reconstructs the image by applying inverse operations to the bitstream in the reverse order.

Introduction

Discrete Cosine Transformation (DCT)

The original image x_{n_1,n_2} is divided into non-overlapping blocks $x_{b_1,b_2;i_1,i_2}$.

→ DCT coefficients $\tilde{x}_{b_1,b_2;u_1,u_2}$



n_1, n_2: spatial index b_1, b_2: block index i_1, i_2: spatial index in block u_1, u_2: DCT index

In the DCT step, the original image x_{n_1,n_2} is first divided into non-overlapping blocks $x_{b_1,b_2;i_1,i_2}$, and they are transformed to the DCT coefficients $\tilde{x}_{b_1,b_2;u_1,u_2}$,

Introduction

Discrete Cosine Transformation (DCT)

The original image x_{n_1,n_2} is divided into non-overlapping blocks $x_{b_1,b_2;i_1,i_2}$.

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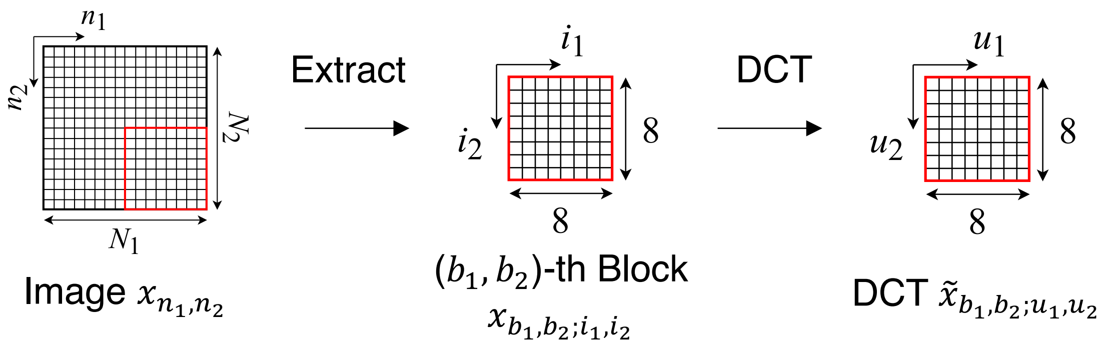


n_1, n_2: spatial index b_1, b_2: block index i_1, i_2: spatial index in block u_1, u_2: DCT index

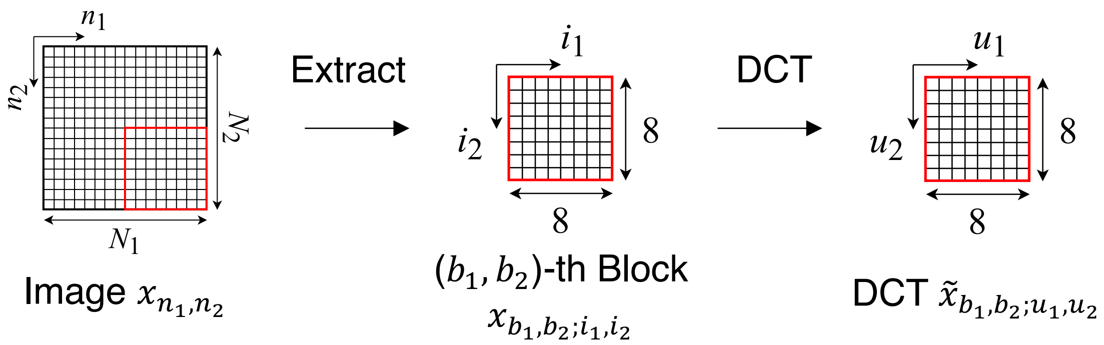
where n_1, n_2 are spatial indices, b_1, b_2 are block indices, i_1, i_2 are spatial indices in a block, and u_1, u_2 are DCT indices.

Introduction

Discrete Cosine Transformation (DCT)

The original image x_{n_1,n_2} is divided into non-overlapping blocks $x_{b_1,b_2;i_1,i_2}$.

→ DCT coefficients $\tilde{x}_{b_1,b_2;u_1,u_2}$



Quantization / Dequantization (DCT coef. → quantization ind. / quantization ind. → DCT coef.)

$$I_{b_1,b_2;u_1,u_2} = \lfloor \tilde{x}_{b_1,b_2;u_1,u_2} \, / \, q_{u_1,u_2} + 0.5 \rfloor \quad (1)$$

$$\tilde{y}_{b_1,b_2;u_1,u_2} = I_{b_1,b_2;u_1,u_2} \cdot q_{u_1,u_2} \quad (2)$$

n_1, n_2: spatial index b_1, b_2: block index i_1, i_2: spatial index in block u_1, u_2: DCT index

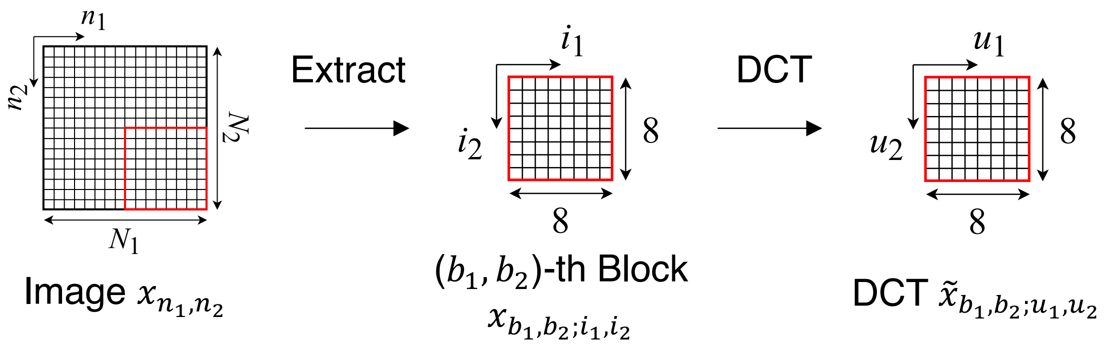
Then, DCT coefficients are quantized by Eq. (1), which transforms DCT coefficients to quantization indices.

Introduction

Discrete Cosine Transformation (DCT)

The original image x_{n_1,n_2} is divided into non-overlapping blocks $x_{b_1,b_2;i_1,i_2}$.

→ DCT coefficients $\tilde{x}_{b_1,b_2;u_1,u_2}$



Quantization / Dequantization (DCT coef. → quantization ind. / quantization ind. → DCT coef.)

$$I_{b_1,b_2;u_1,u_2} = \lfloor \tilde{x}_{b_1,b_2;u_1,u_2} / q_{u_1,u_2} + 0.5 \rfloor \quad (1)$$

$$\tilde{y}_{b_1,b_2;u_1,u_2} = I_{b_1,b_2;u_1,u_2} \cdot q_{u_1,u_2} \quad (2)$$

n_1, n_2: spatial index b_1, b_2: block index i_1, i_2: spatial index in block u_1, u_2: DCT index

The dequantization is defined by Eq. (2), which reproduces DCT coefficients.

Introduction

Entropy Coding

- The variance of the magnitude $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$ is typically small → compressible

In entropy coding, because the variance of the magnitude is typically small,
they can be efficiently compressed.

Introduction

Entropy Coding

- The variance of the magnitude $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$ is typically small → compressible
- Sign information $\mathrm{sgn}\left(\tilde{y}_{b_1,b_2;u_1,u_2}\right)$ is equiprobable → incompressible

On the other hand, because the probability of their sign bits are equivalent,
they cannot be compressed by entropy coding theoretically.

Introduction

Entropy Coding

- The variance of the magnitude $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$ is typically small → compressible
- Sign information $\operatorname{sgn}\left(\tilde{y}_{b_1,b_2;u_1,u_2}\right)$ is equiprobable → incompressible

Our goal: efficient lossless compression of $\operatorname{sgn}\left(\tilde{y}_{b_1,b_2;u_1,u_2}\right)$

In our study, we attempt to losslessly compress the sign information.

Agenda

We then elaborate the proposed sign compression method.

Agenda

1. Introduction

2. Proposed Method
   2.1. Encoder and Decoder
   2.2. Sign Retrieval and Its Solution

3. Experimental Results

4. Conclusion

Before introducing our sign retrieval, we define our encoder and decoder.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

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Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Encoder

1. The sign information of all the AC components are excluded from a bitstream.

In the encoder, the sign information of all the AC components are excluded from a bitstream.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Encoder

1. The sign information of all the AC components are excluded from a bitstream.
   (In other words, only the magnitudes $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$ are first compressed by entropy coding.)

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

In other words, only the magnitudes are first compressed by entropy coding.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Encoder

1. The sign information of all the AC components are excluded from a bitstream.
   (In other words, only the magnitudes $|\tilde{y}_{b_1,b_2;u_1,u_2}|$ are first compressed by entropy coding.)
2. The encoder then performs the sign retrieval to retrieve the signs of $|\tilde{y}_{b_1,b_2;u_1,u_2}|$.

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

The encoder then performs the sign retrieval to retrieval the sign of DCT coefficients.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Encoder

1. The sign information of all the AC components are excluded from a bitstream.
   (In other words, only the magnitudes $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$ are first compressed by entropy coding.)
2. The encoder then performs the sign retrieval to retrieve the signs of $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$.
3. Finally, since there is possibility that retrieved signs will be incorrect, we append the residual

$$e_{b_1,b_2;u_1,u_2} = \mathrm{sgn}\left(\tilde{y}_{b_1,b_2;u_1,u_2}\right) \oplus \mathrm{ret\_sgn}_{b_1,b_2;u_1,u_2} \quad (3)$$

   to the bitstream, where $\mathrm{ret\_sgn}_{b_1,b_2;u_1,u_2}$ is the retrieved sign and $\oplus$ is the XOR operator.

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

Finally, since there is possibility that retrieved signs will be incorrect,
we append the residual in Eq. (3) to the bitstream.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Encoder

1. The sign information of all the AC components are excluded from a bitstream.
   (In other words, only the magnitudes $|\tilde{y}_{b_1,b_2;u_1,u_2}|$ are first compressed by entropy coding.)
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   to the bitstream, where $\mathrm{ret\_sgn}_{b_1,b_2;u_1,u_2}$ is the retrieved sign and $\oplus$ is the XOR operator.

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

$\mathrm{ret\_sgn}_{b_1,b_2;u_1,u_2}$ represents the retrieved sign bits by the sign retrieval, and $\oplus$ is the XOR operator.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Decoder

1. The decoder first purses the bitstream to obtain $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$ and $e_{b_1,b_2;u_1,u_2}$.

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

On the other hand,
the decoder first purses the bitstream to obtain the magnitudes and error correction bits.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Decoder

1. The decoder first purses the bitstream to obtain $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$ and $e_{b_1,b_2;u_1,u_2}$.
2. The sign information is then retrieved via the sign retrieval using only $\left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|$.

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

The sign information is then retrieved via the sign retrieval using only the magnitudes.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Decoder

1. The decoder first purses the bitstream to obtain $|\tilde{y}_{b_1,b_2;u_1,u_2}|$ and $e_{b_1,b_2;u_1,u_2}$.
2. The sign information is then retrieved via the sign retrieval using only $|\tilde{y}_{b_1,b_2;u_1,u_2}|$.
3. Finally, the retrieved signs including errors are corrected by $e_{b_1,b_2;u_1,u_2}$.

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

Finally, the retrieved signs including errors are corrected by the error correction bits.

Proposed Method, Encoder and Decoder

- We modify a bitstream standardized in JPEG.

Decoder

1. The decoder first purses the bitstream to obtain $|\tilde{y}_{b_1,b_2;u_1,u_2}|$ and $e_{b_1,b_2;u_1,u_2}$.
2. The sign information is then retrieved via the sign retrieval using only $|\tilde{y}_{b_1,b_2;u_1,u_2}|$.
3. Finally, the retrieved signs including errors are corrected by $e_{b_1,b_2;u_1,u_2}$.

- If the sign bits are retrieved correctly to some extent.

  → The residual information hopefully has many zeros but few ones (compressible).

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

If the sign bits are retrieved correctly to some extent,
the residual information hopefully has many zeros but few ones, which is compressible.

Agenda

We now elaborate the proposed sign retrieval method.

Proposed Methdo, Sign Retrieval and Its Solution

Phase Retieval

$$\text{Find} \quad \text{phase}\left(\hat{x}_{k_1,k_2}\right) \quad \text{from} \quad \left|\hat{x}_{k_1,k_2}\right|, \quad \forall k_1, k_2 \tag{4}$$

The phase retrieval is an optimization problem such that
we find the true phase from magnitude only,

Proposed Methdo, Sign Retrieval and Its Solution

Phase Retieval

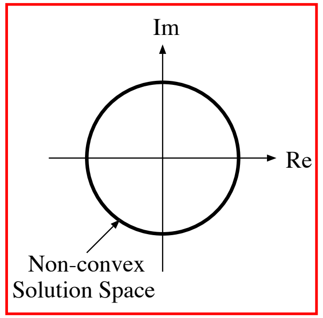
$$\text{Find} \quad \text{phase}\left(\hat{x}_{k_1,k_2}\right) \quad \text{from} \quad \left|\hat{x}_{k_1,k_2}\right|, \quad \forall k_1, k_2 \tag{4}$$

where $\hat{x}_{k_1,k_2}$ is the discrete Fourier transform of the image x_{n_1,n_2}.

Proposed Methdo, Sign Retrieval and Its Solution

Phase Retieval

$$\text{Find} \quad \text{phase}\left(\hat{x}_{k_1,k_2}\right) \quad \text{from} \quad \left|\hat{x}_{k_1,k_2}\right|, \qquad \forall k_1, k_2 \tag{4}$$

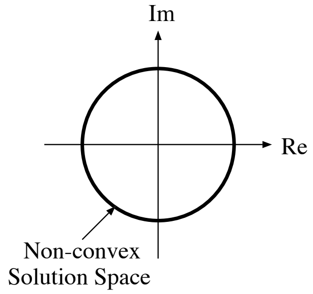


Geometrically, we have to find the phase from a complex circle, which is a non-convex solution space.

Proposed Methdo, Sign Retrieval and Its Solution

Phase Retieval

$$\text{Find} \quad \text{phase}\left(\hat{x}_{k_1,k_2}\right) \quad \text{from} \quad \left|\hat{x}_{k_1,k_2}\right|, \quad \forall k_1, k_2 \tag{4}$$

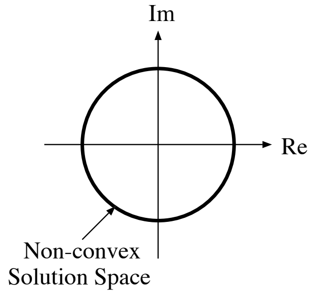


By restricting the solution space to the real domain,
and the changing the DFT coefficients to the DCT ones,

Proposed Methdo, Sign Retrieval and Its Solution

Phase Retieval

$$\text{Find} \quad \text{phase}\left(\hat{x}_{k_1,k_2}\right) \quad \text{from} \quad \left|\hat{x}_{k_1,k_2}\right|, \quad \forall k_1, k_2 \tag{4}$$



Sign Retrieval

$$\text{Find} \quad \text{sgn}\left(\tilde{y}_{b_1,b_2;u_1,u_2}\right) \quad \text{from} \quad \left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|, \quad \forall b_1, b_2, u_1, u_2 \tag{5}$$

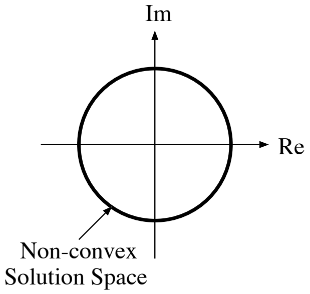
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

we have the sign retrieval problem, which attempts to find the true sign from the DCT magnitude.

Proposed Methdo, Sign Retrieval and Its Solution

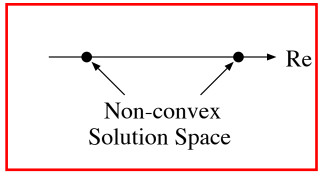
Phase Retieval

$$\text{Find} \quad \text{phase}\left(\hat{x}_{k_1,k_2}\right) \quad \text{from} \quad \left|\hat{x}_{k_1,k_2}\right|, \qquad \forall k_1, k_2 \tag{4}$$



Sign Retrieval

$$\text{Find} \quad \text{sgn}\left(\tilde{y}_{b_1,b_2;u_1,u_2}\right) \quad \text{from} \quad \left|\tilde{y}_{b_1,b_2;u_1,u_2}\right|, \qquad \forall b_1, b_2, u_1, u_2 \tag{5}$$



$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

We remark that the sign retrieval problem is a non-convex problem,
so it cannot be solved within polynomial time.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

To overcome this difficulty, we exploit the method of Goldstein and Studar, which is referred to as PhaseMax.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z} \in \mathrm{R}^{N_1 \times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \mathrm{s.t.} \quad \left| z_{k_1,k_2} \right| \leq \left| \hat{x}_{k_1,k_2} \right|, \quad \forall k_1, k_2 \tag{6}$$

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

PhaseMax is defined by Eq. (6), where $\boldsymbol{\phi}$ is the anchor vector.

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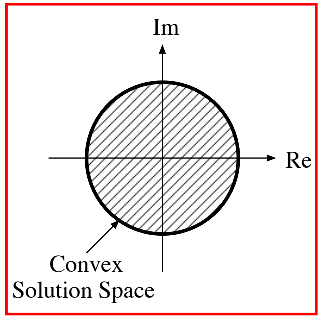
PhaseMax Method (Goldstein and Studar, 2018)

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in \mathrm{R}^{N_1\times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z}\rangle \quad \mathrm{s.t.} \quad \left|z_{k_1,k_2}\right| \leq \left|\hat{x}_{k_1,k_2}\right|, \quad \forall k_1, k_2 \tag{6}$$



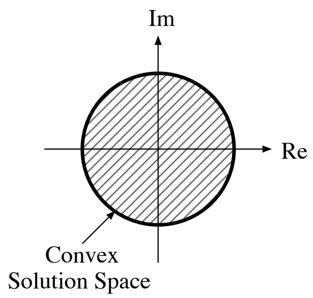
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

Geometrically, the solution space of Eq. (6) is a convex disk, and Eq. (6) is thus solvable within polynomial time.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in\mathrm{R}^{N_1\times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \mathrm{s.t.} \quad |z_{k_1,k_2}| \leq |\hat{x}_{k_1,k_2}|, \quad \forall k_1, k_2 \tag{6}$$



- Assume $\langle \boldsymbol{x}, \boldsymbol{\phi} \rangle = C$, $\boldsymbol{x}$ is the vectorized version of the original iamge.

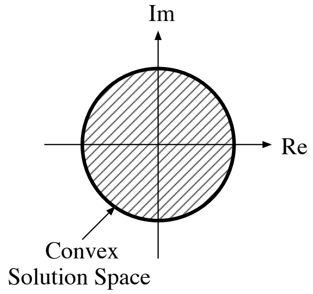
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

If the inner product of the original image $\boldsymbol{x}$ and the anchor vector $\boldsymbol{\phi}$ is a constant C,

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z} \in \mathrm{R}^{N_1 \times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \mathrm{s.t.} \quad \left| z_{k_1,k_2} \right| \leq \left| \hat{x}_{k_1,k_2} \right|, \quad \forall k_1, k_2 \tag{6}$$



- Assume $\langle \boldsymbol{x}, \boldsymbol{\phi} \rangle = C$, $\boldsymbol{x}$ is the vectorized version of the original iamge.
- Assume $\hat{x}_{k_1,k_2}$ is oversampled, $\hat{x}_{k_1,k_2}$ is a coefficient of the overcomplete DFT.

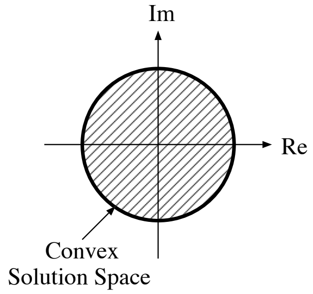
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

and $\hat{x}_{k_1,k_2}$ is a coefficient of the overcomplete DFT,

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in\mathrm{R}^{N_1\times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z}\rangle \quad \mathrm{s.t.} \quad |z_{k_1,k_2}| \leq |\hat{x}_{k_1,k_2}|, \quad \forall k_1, k_2 \tag{6}$$



- Assume $\langle \boldsymbol{x}, \boldsymbol{\phi}\rangle = C$, $\boldsymbol{x}$ is the vectorized version of the original iamge.
- Assume $\hat{x}_{k_1,k_2}$ is oversampled, $\hat{x}_{k_1,k_2}$ is a coefficient of the overcomplete DFT.

→ Solutions of the original (non-convex) phase retrieval) and Eq. (6) are equivalent with the probability $1 - O(\exp(-C)^{2/5})$.

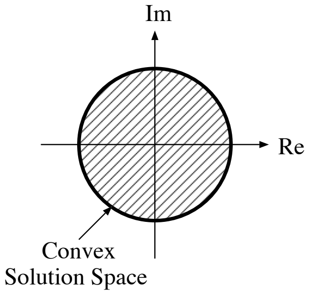
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

solutions of the original non-convex phase retrieval and the PhaseMax are probably equivalent.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z} \in \mathrm{R}^{N_1 \times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \mathrm{s.t.} \quad \left| z_{k_1,k_2} \right| \leq \left| \hat{x}_{k_1,k_2} \right|, \quad \forall k_1, k_2 \tag{6}$$



Assumption: $\hat{x}_{k_1,k_2}$ is oversampled.

Regularized SignMax Method

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z} \in \mathrm{R}^{N_1 \times N_2}} \sum_{b_1,b_2} \langle \boldsymbol{\phi}_{b_1,b_2}, \boldsymbol{z}_{b_1,b_2} \rangle - \lambda \left\| \boldsymbol{\Psi} \mathbf{z} \right\|_1 \ \mathrm{s.t.} \ \left| \tilde{y}_{b_1,b_2;u_1,u_2} \right| \leq \left| \tilde{y}_{b_1,b_2;u_1,u_2} \right|, \forall b_1, b_2, u_1, u_2 \tag{7}$$

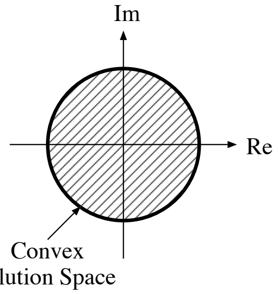
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

We also relax the sign retrieval problem as in Eq. (7),
where $\boldsymbol{\Psi}$ is a sparsity promoting matrix.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

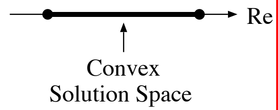
$$\boldsymbol{z}^* = \text{argmax}_{\boldsymbol{z} \in \mathrm{R}^{N_1 \times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \text{s.t.} \quad |z_{k_1,k_2}| \leq |\hat{x}_{k_1,k_2}|, \quad \forall k_1, k_2 \tag{6}$$



Assumption: $\hat{x}_{k_1,k_2}$ is oversampled.

Regularized SignMax Method

$$\boldsymbol{z}^* = \text{argmax}_{\boldsymbol{z} \in \mathrm{R}^{N_1 \times N_2}} \sum_{b_1,b_2} \langle \boldsymbol{\phi}_{b_1,b_2}, \boldsymbol{z}_{b_1,b_2} \rangle - \lambda \|\boldsymbol{\Psi}\mathbf{z}\|_1 \ \text{s.t.} \ |\tilde{y}_{b_1,b_2;u_1,u_2}| \leq |\tilde{y}_{b_1,b_2;u_1,u_2}|, \forall b_1, b_2, u_1, u_2 \tag{7}$$



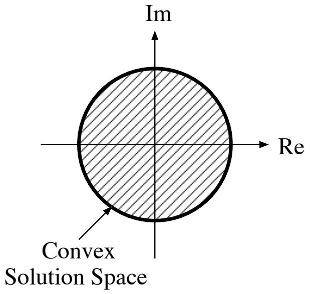
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

Because the constraint is convex, we can solve Eq. (7) within polynomial time.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

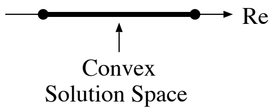
$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in\mathrm{R}^{N_1\times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \mathrm{s.t.} \quad |z_{k_1,k_2}| \le |\hat{x}_{k_1,k_2}|, \quad \forall k_1, k_2 \qquad (6)$$



Assumption: $\hat{x}_{k_1,k_2}$ is oversampled.

Regularized SignMax Method

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in\mathrm{R}^{N_1\times N_2}} \textstyle\sum_{b_1,b_2} \langle \boldsymbol{\phi}_{b_1,b_2}, \boldsymbol{z}_{b_1,b_2} \rangle - \lambda \, \|\boldsymbol{\Psi}\mathbf{z}\|_1 \;\; \mathrm{s.t.} \;\; |\tilde{y}_{b_1,b_2;u_1,u_2}| \le |\tilde{y}_{b_1,b_2;u_1,u_2}|, \forall b_1, b_2, u_1, u_2 \qquad (7)$$



- A regularization term was appended based on the compressed sensing theory.

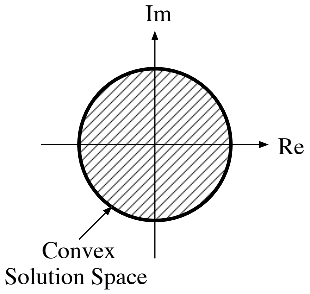
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients $\quad b_1, b_2$: block indices $\quad u_1, u_2$: DCT indices

We here appended a regularization term based on the compressed sensing theory.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

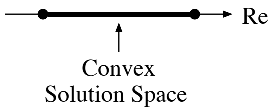
$$z^* = \operatorname{argmax}_{z \in \mathbb{R}^{N_1 \times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \text{s.t.} \quad |z_{k_1,k_2}| \leq |\hat{x}_{k_1,k_2}|, \quad \forall k_1, k_2 \quad (6)$$



Assumption: $\hat{x}_{k_1,k_2}$ is oversampled.

Regularized SignMax Method

$$z^* = \operatorname{argmax}_{z \in \mathbb{R}^{N_1 \times N_2}} \sum_{b_1,b_2} \langle \boldsymbol{\phi}_{b_1,b_2}, \boldsymbol{z}_{b_1,b_2} \rangle - \lambda \|\boldsymbol{\Psi z}\|_1 \quad \text{s.t.} \quad |\tilde{y}_{b_1,b_2;u_1,u_2}| \leq |\tilde{y}_{b_1,b_2;u_1,u_2}|, \forall b_1, b_2, u_1, u_2 \quad (7)$$



- A regularization term was appended based on the compressed sensing theory. (An underdetermined system can be exactly solved by the L_1-norm regularization.)

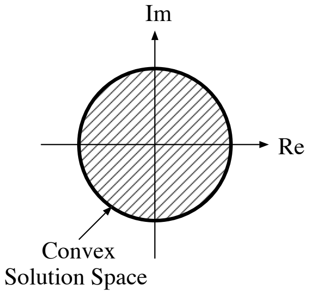
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

This theory states that an optimization problem formulated by undersampled data can be exactly solved by the L_1-norm regularization.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

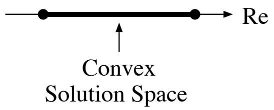
$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in\mathrm{R}^{N_1\times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z} \rangle \quad \mathrm{s.t.} \quad |z_{k_1,k_2}| \le |\hat{x}_{k_1,k_2}|, \quad \forall k_1, k_2 \qquad (6)$$



Assumption: $\hat{x}_{k_1,k_2}$ is oversampled.

Regularized SignMax Method

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in\mathrm{R}^{N_1\times N_2}} \sum_{b_1,b_2} \langle \boldsymbol{\phi}_{b_1,b_2}, \boldsymbol{z}_{b_1,b_2} \rangle - \lambda \|\boldsymbol{\Psi}\mathbf{z}\|_1 \quad \mathrm{s.t.} \quad |\tilde{y}_{b_1,b_2;u_1,u_2}| \le |\tilde{y}_{b_1,b_2;u_1,u_2}|, \forall b_1, b_2, u_1, u_2 \qquad (7)$$



- A regularization term was appended based on the compressed sensing theory. (An underdetermined system can be exactly solved by the L_1-norm regularization.)

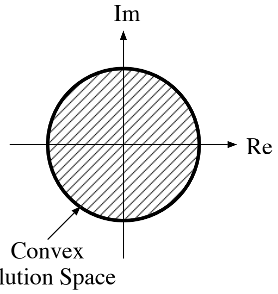
$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

So, the assumption in the PhaseMax can be ignored in the regularized SignMax.

Proposed Methdo, Sign Retrieval and Its Solution

PhaseMax Method (Goldstein and Studar, 2018)

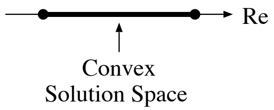
$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in \mathrm{R}^{N_1\times N_2}} \langle \boldsymbol{\phi}, \boldsymbol{z}\rangle \quad \mathrm{s.t.} \quad |z_{k_1,k_2}| \leq |\hat{x}_{k_1,k_2}|, \quad \forall k_1, k_2 \quad (6)$$



Assumption: $\hat{x}_{k_1,k_2}$ is oversampled.

Regularized SignMax Method

$$\boldsymbol{z}^* = \mathrm{argmax}_{\boldsymbol{z}\in \mathrm{R}^{N_1\times N_2}} \sum_{b_1,b_2} \langle \boldsymbol{\phi}_{b_1,b_2}, \boldsymbol{z}_{b_1,b_2}\rangle - \lambda \|\boldsymbol{\Psi}\mathbf{z}\|_1 \ \ \mathrm{s.t.} \ \ |\tilde{y}_{b_1,b_2;u_1,u_2}| \leq |\tilde{y}_{b_1,b_2;u_1,u_2}|, \forall b_1, b_2, u_1, u_2 \quad (7)$$



- A regularization term was appended based on the compressed sensing theory. (An underdetermined system can be exactly solved by the L_1-norm regularization.)

$\tilde{y}_{b_1,b_2;u_1,u_2}$: DCT coefficients b_1, b_2: block indices u_1, u_2: DCT indices

We employed the 12-th order Symmlet transformation matrix as $\boldsymbol{\Psi}$.

Proposed Methdo, Sign Retrieval and Its Solution

Solution to Regularized SignMax Method

- Cascaded Fienup method

for $\theta = 1, \cdots, \Theta$

Fienup Method

$$\mathbf{f}^*_{[\theta+1]} = \mathbf{\Psi}^{\mathrm{t}} \left(\mathrm{sgn}\left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]}\right) \cdot \left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]} - \lambda\right)_+ \right) \quad (8)$$

Proximal operator of L_1 norm

$$\mathbf{g}^*_{[\theta+1]} = \mathbf{f}^*_{[\theta+1]} + \frac{1}{\mu}\boldsymbol{\phi} \quad (9)$$

Proximal operator of inner product

$$\mathbf{z}^*_{[\theta+1]} = \mathrm{proj}_C\left(\mathbf{g}^*_{[\theta+1]}\right) \quad (10)$$

Projection onto the DCT constraint

The solution to regularized SignMax problem is obtained by our Cascaded Fienup Method.

Proposed Methdo, Sign Retrieval and Its Solution

Solution to Regularized SignMax Method

- Cascaded Fienup method

for $\theta = 1, \cdots, \Theta$

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$$\mathbf{f}^*_{[\theta+1]} = \mathbf{\Psi}^{\mathrm{t}} \left(\mathrm{sgn}\left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]}\right) \cdot \left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]} - \lambda\right)_+ \right) \quad (8)$$

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Proximal operator of inner product

$$\mathbf{z}^*_{[\theta+1]} = \mathrm{proj}_C\left(\mathbf{g}^*_{[\theta+1]}\right) \quad (10)$$

Projection onto the DCT constraint

The Fienup method is one of solution techniques for phase retrieval.

Proposed Methdo, Sign Retrieval and Its Solution

Solution to Regularized SignMax Method

- Cascaded Fienup method

for $\theta = 1, \cdots, \Theta$

Fienup Method

$$\mathbf{f}^*_{[\theta+1]} = \mathbf{\Psi}^{\mathrm{t}} \left(\mathrm{sgn}\left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]}\right) \cdot \left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]} - \lambda\right)_+ \right) \quad (8)$$

Proximal operator of L_1 norm

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Proximal operator of inner product

$$\mathbf{z}^*_{[\theta+1]} = \mathrm{proj}_C\left(\mathbf{g}^*_{[\theta+1]}\right) \quad (10)$$

Projection onto the DCT constraint

For regularized SignMax, the Fienup method includes the proximal operator of L_1 norm, the proximal operator of the inner product, and the projection onto the DCT constraint.

Proposed Methdo, Sign Retrieval and Its Solution

Solution to Regularized SignMax Method

- Cascaded Fienup method

for $\gamma = 1, \cdots, \Gamma$

for $\theta = 1, \cdots, \Theta$

Fienup Method

$$\mathbf{f}^*_{[\theta+1]} = \boldsymbol{\Psi}^{\mathrm{t}} \left(\mathrm{sgn}\left(\boldsymbol{\Psi}\mathbf{z}^*_{[\theta]}\right) \cdot \left(\boldsymbol{\Psi}\mathbf{z}^*_{[\theta]} - \lambda\right)_+ \right) \quad (8)$$

Proximal operator of L_1 norm

$$\mathbf{g}^*_{[\theta+1]} = \mathbf{f}^*_{[\theta+1]} + \frac{1}{\mu} \boldsymbol{\phi}_{[\gamma]} \quad (9)$$

Proximal operator of inner product

$$\mathbf{z}^*_{[\theta+1]} = \mathrm{proj}_C\left(\mathbf{g}^*_{[\theta+1]}\right) \quad (10)$$

Projection onto the DCT constraint

$$\boldsymbol{\phi}_{[\gamma+1]} = \mathbf{z}^*_{[\theta+1]} \quad (11)$$

Update anchor vector

Because the anchor vector largely affects the reconstruction quality of images as in PhaseMax, the anchor vector should be close to the original image x.

Proposed Methdo, Sign Retrieval and Its Solution

Solution to Regularized SignMax Method

- Cascaded Fienup method

for $\gamma = 1, \cdots, \Gamma$

for $\theta = 1, \cdots, \Theta$

Fienup Method

$$\mathbf{f}^*_{[\theta+1]} = \mathbf{\Psi}^{\mathrm{t}} \left(\mathrm{sgn}\left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]}\right) \cdot \left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]} - \lambda\right)_+ \right) \quad (8)$$

Proximal operator of L_1 norm

$$\mathbf{g}^*_{[\theta+1]} = \mathbf{f}^*_{[\theta+1]} + \frac{1}{\mu} \boldsymbol{\phi}_{[\gamma]} \quad (9)$$

Proximal operator of inner product

$$\mathbf{z}^*_{[\theta+1]} = \mathrm{proj}_C\left(\mathbf{g}^*_{[\theta+1]}\right) \quad (10)$$

Projection onto the DCT constraint

$$\boldsymbol{\phi}_{[\gamma+1]} = \mathbf{z}^*_{[\theta+1]} \quad (11)$$

Update anchor vector

Because $\mathbf{z}^*_{[\theta+1]}$ may be closer to the original image than the initial guess $\mathbf{z}^*_{[0]}$, the anchor vector is updated as in Eq. (11).

Proposed Methdo, Sign Retrieval and Its Solution

Solution to Regularized SignMax Method

- Cascaded Fienup method

for $\gamma = 1, \cdots, \Gamma$

for $\theta = 1, \cdots, \Theta$

Fienup Method

$$\mathbf{f}^*_{[\theta+1]} = \mathbf{\Psi}^{\mathrm{t}} \left(\mathrm{sgn}\left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]}\right) \cdot \left(\mathbf{\Psi}\mathbf{z}^*_{[\theta]} - \lambda\right)_+ \right) \quad (8)$$

Proximal operator of L_1 norm

$$\mathbf{g}^*_{[\theta+1]} = \mathbf{f}^*_{[\theta+1]} + \frac{1}{\mu} \boldsymbol{\phi}_{[\gamma]} \quad (9)$$

Proximal operator of inner product

$$\mathbf{z}^*_{[\theta+1]} = \mathrm{proj}_C\left(\mathbf{g}^*_{[\theta+1]}\right) \quad (10)$$

Projection onto the DCT constraint

$$\boldsymbol{\phi}_{[\gamma+1]} = \mathbf{z}^*_{[\theta+1]} \quad (11)$$

Update anchor vector

They are all of the proposed sign compression method.

Agenda

1. Introduction
2. Proposed Method
   2.1. Encoder and Decoder
   2.2. Sign Retrieval and Its Solution
3. Experimental Results
4. Conclusion

To verify the effectiveness of our method, we mention our experiments.

Experimental Results

- We implemented our method in JPEG.

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Experimental Results

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- Our method is compared with (Penomarenko et al., 2007) and JPEG.

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Experimental Results

- We implemented our method in JPEG.
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(Penomarenko et al, 2007):

1. The sign bits of $\tilde{y}_{b_1,b_2;u_1,u_2}$ is predicted from neighbor blocks.

The method of Penomarenko et al. first predicts the sign bit from neighbor blocks,

Experimental Results

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- Our method is compared with (Penomarenko et al., 2007) and JPEG.

(Penomarenko et al, 2007):

1. The sign bits of $\tilde{y}_{b_1,b_2;u_1,u_2}$ is predicted from neighbor blocks.
2. Residuals are transmitted instead of the original sign bits.

and residuals are transmitted instead of the original sign bits.

Experimental Results

- We implemented our method in JPEG.
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(Penomarenko et al, 2007):

1. The sign bits of $\tilde{y}_{b_1,b_2;u_1,u_2}$ is predicted from neighbor blocks.
2. Residuals are transmitted instead of the original sign bits.



The three images of the size 1024 x 1024 were compressed by varying the quality factor ranging from 20 to 80.

Experimental Results

- We implemented our method in JPEG.
- Our method is compared with (Penomarenko et al., 2007) and JPEG.

(Penomarenko et al, 2007):

1. The sign bits of $\tilde{y}_{b_1,b_2;u_1,u_2}$ is predicted from neighbor blocks.
2. Residuals are transmitted instead of the original sign bits.

- All the methods yield the same error against the original image
  → the entropy [bpp] was evaluated.

Because all the methods yield the same error against the original image,
we evaluate the entropy required for compressing the sign bits.

Experimental Results

- We implemented our method in JPEG.
- Our method is compared with (Penomarenko et al., 2007) and JPEG.

(Penomarenko et al, 2007):

1. The sign bits of $\tilde{y}_{b_1,b_2;u_1,u_2}$ is predicted from neighbor blocks.
2. Residuals are transmitted instead of the original sign bits.

- All the methods yield the same error against the original image
  → the entropy [bpp] was evaluated.

In JPEG, the required information was the original sign bits,
while our method and Penomarenko et al. were residual bits.

Experimental Results

- We implemented our method in JPEG.
- Our method is compared with (Penomarenko et al., 2007) and JPEG.

(Penomarenko et al, 2007):

1. The sign bits of $\tilde{y}_{b_1,b_2;u_1,u_2}$ is predicted from neighbor blocks.
2. Residuals are transmitted instead of the original sign bits.

- All the methods yield the same error against the original iamge
  $\rightarrow$ the entropy [bpp] was evaluated.
- $\lambda = 1.0$ (regularization param.), $\mu = 0.1$ (prox. Inner product), $\Gamma = 1, 2, 3$ (num. cascading), and $\Theta = 300$ (num. iter. Fienup)

In our method, the regularization parameter $\lambda = 1.0$,
μ in the proximal operator of the inner product was 0.1,

Experimental Results

- We implemented our method in JPEG.
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(Penomarenko et al, 2007):

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  $\rightarrow$ the entropy [bpp] was evaluated.
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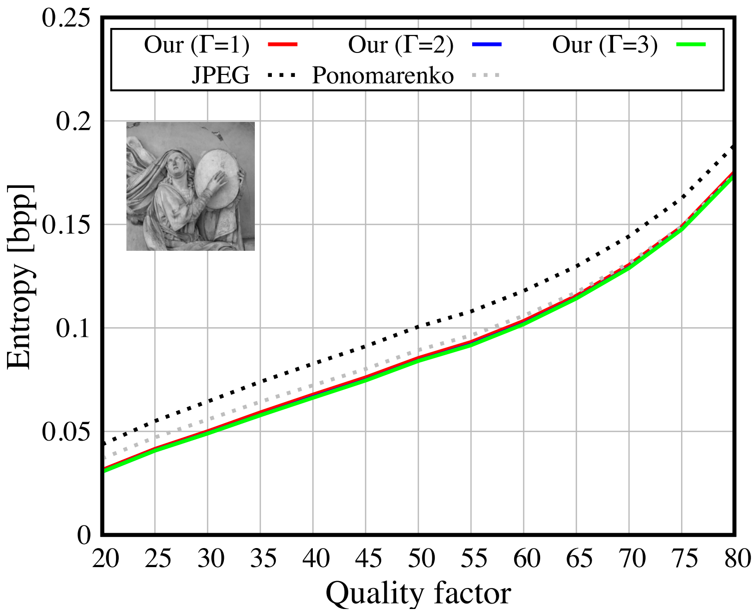
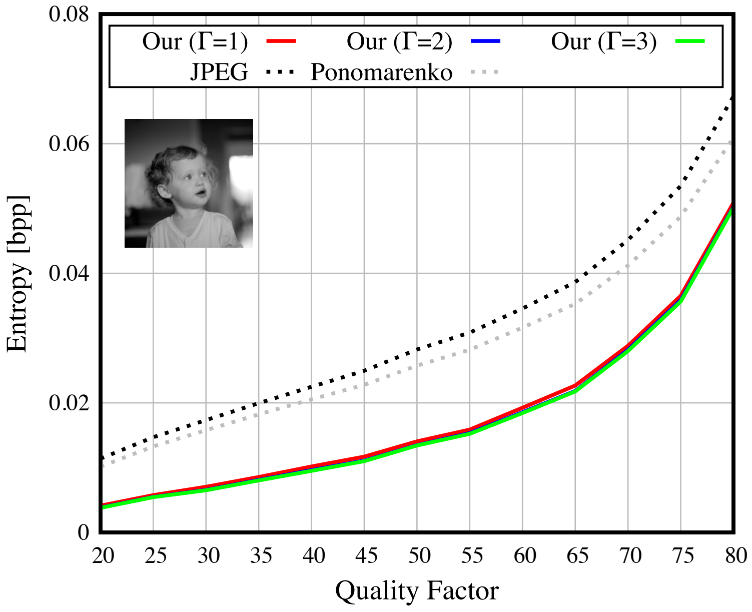
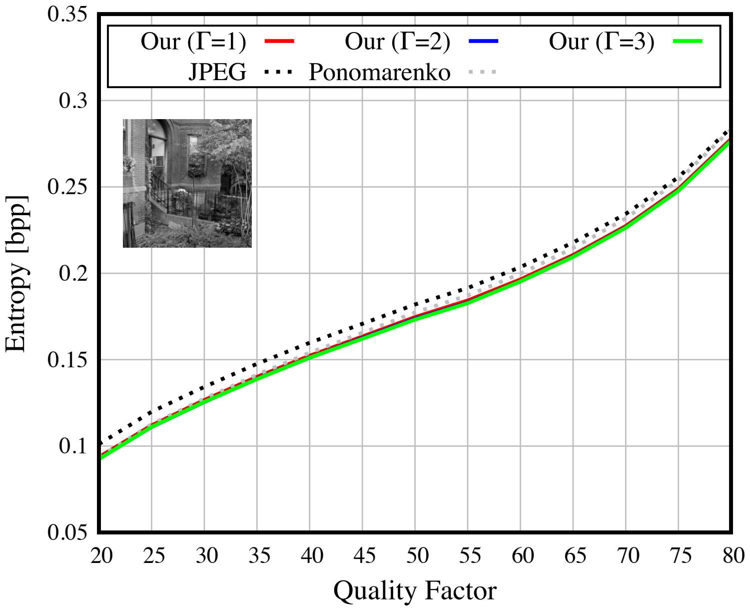
the number of cascading was varied from 1 to 3,
and the number of iterations in the Fienup method was 300 fixed.

Experimental Results

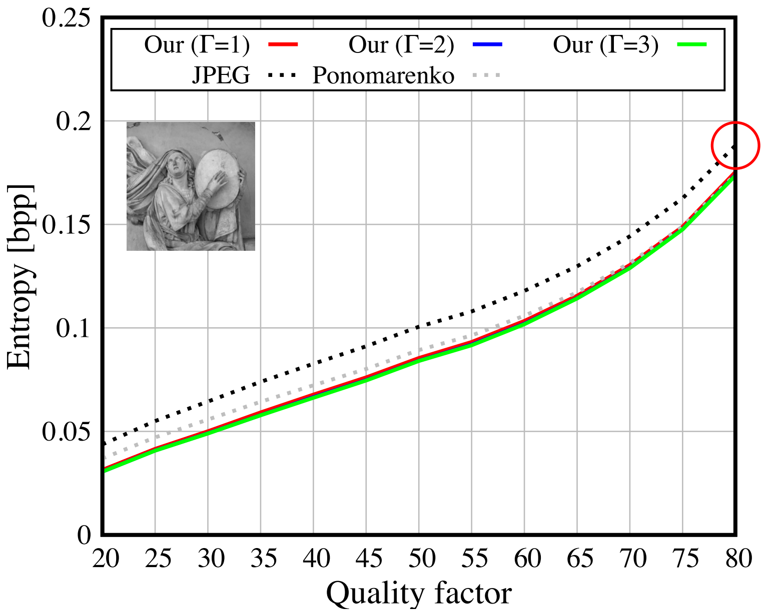


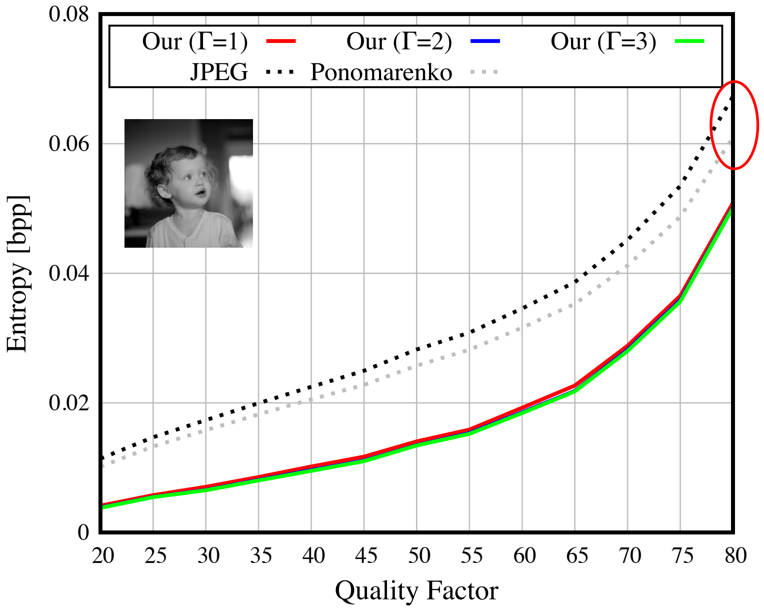


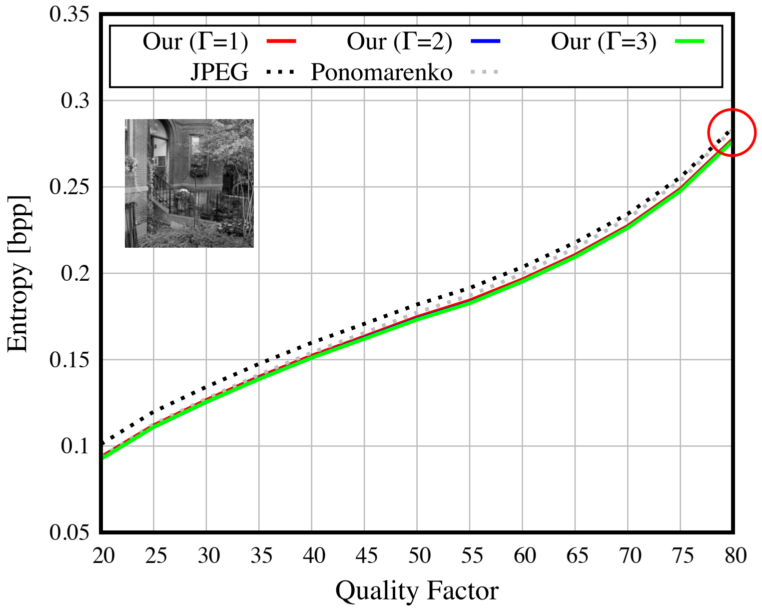


These figures show the entropy to transmit the sign information of the DCT coefficients by each method.

Experimental Results

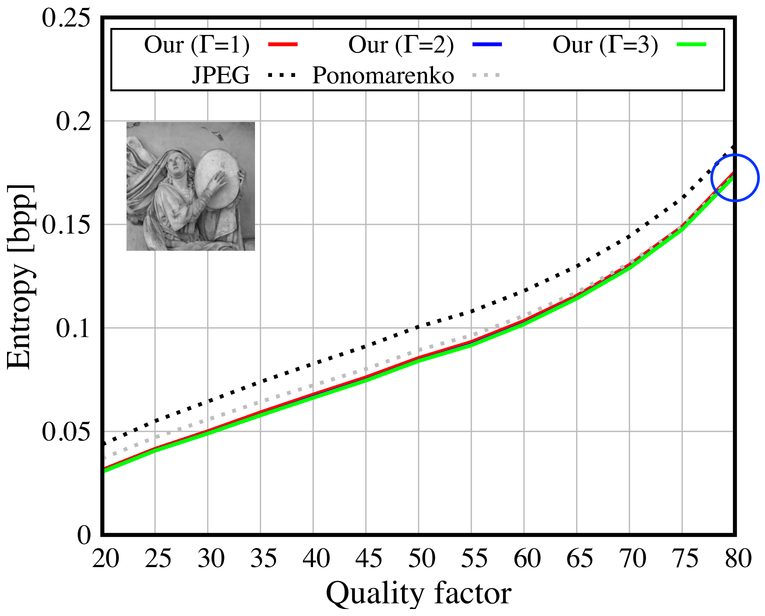


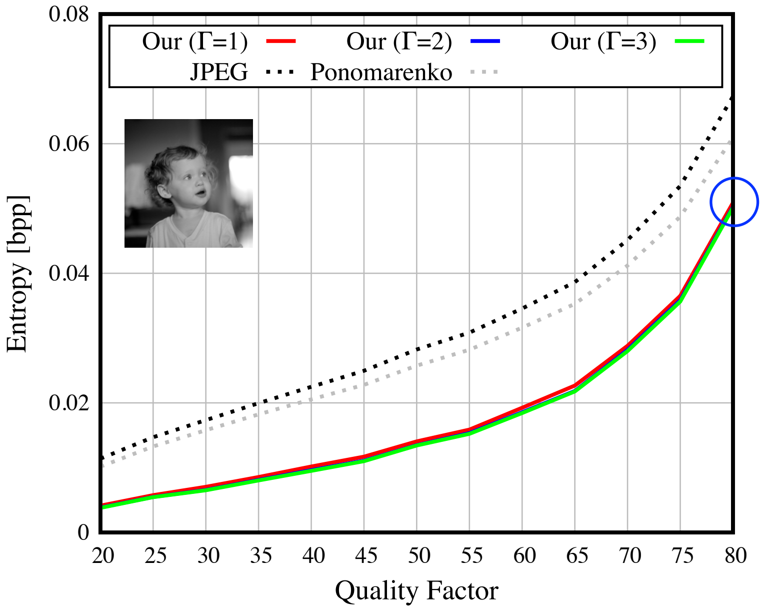


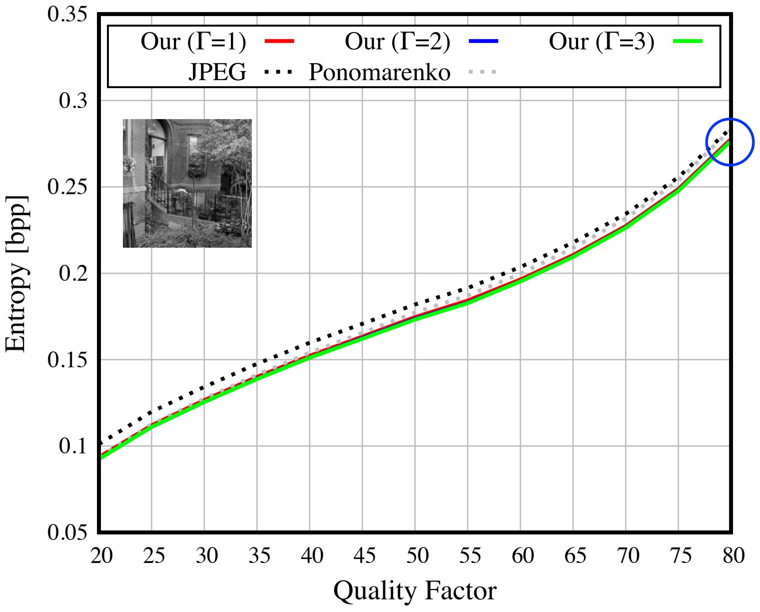


The dashed lines are JPEG and a previous sign compression technique,

Experimental Results

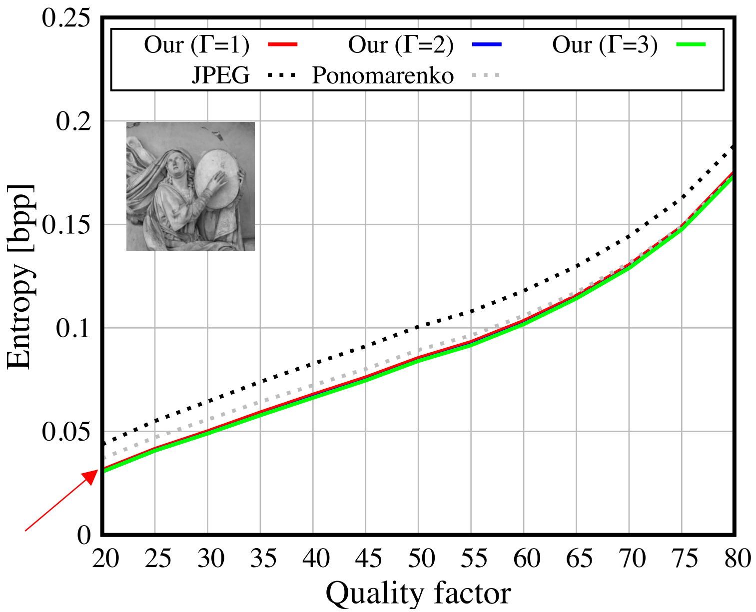


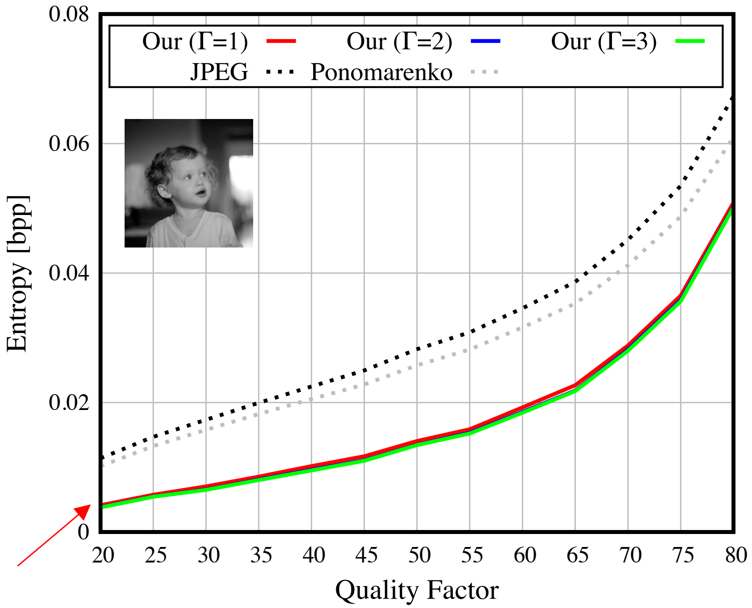


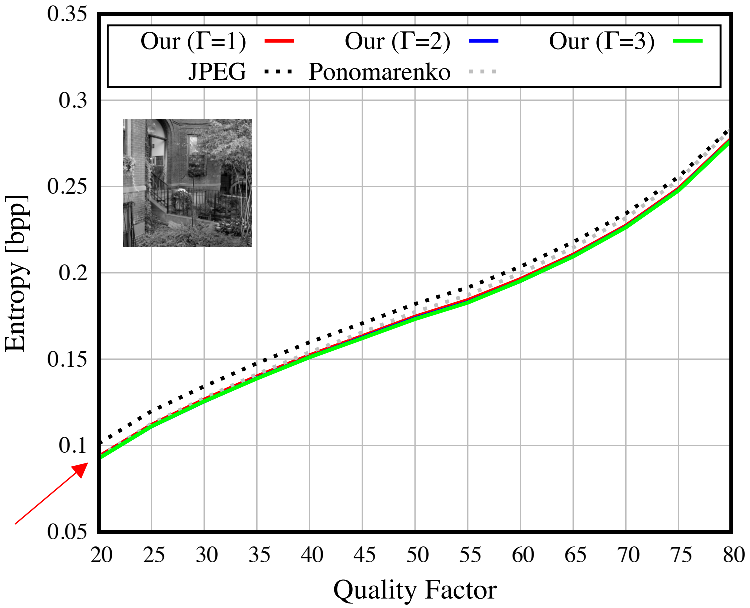


and the solid lines are our results.

Experimental Results



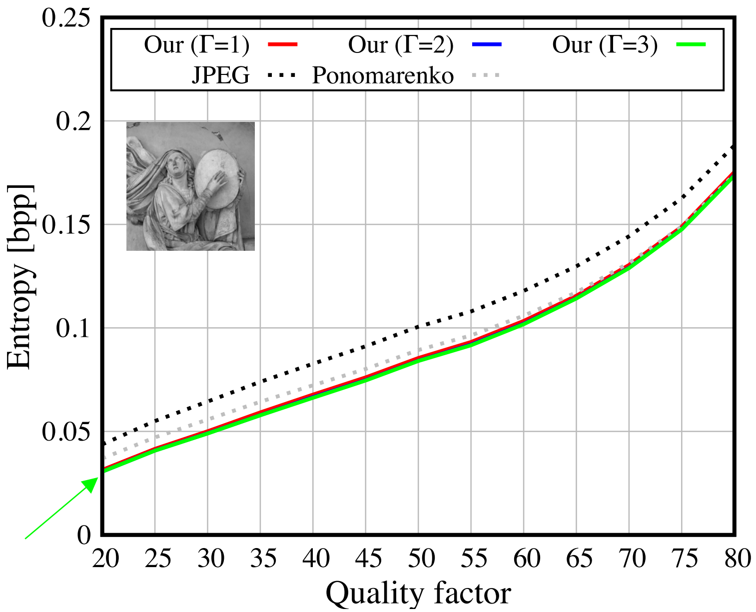


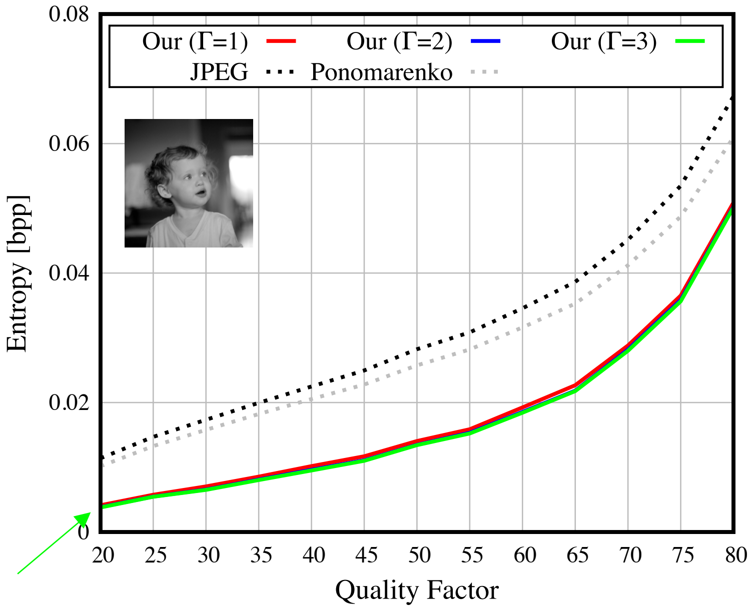


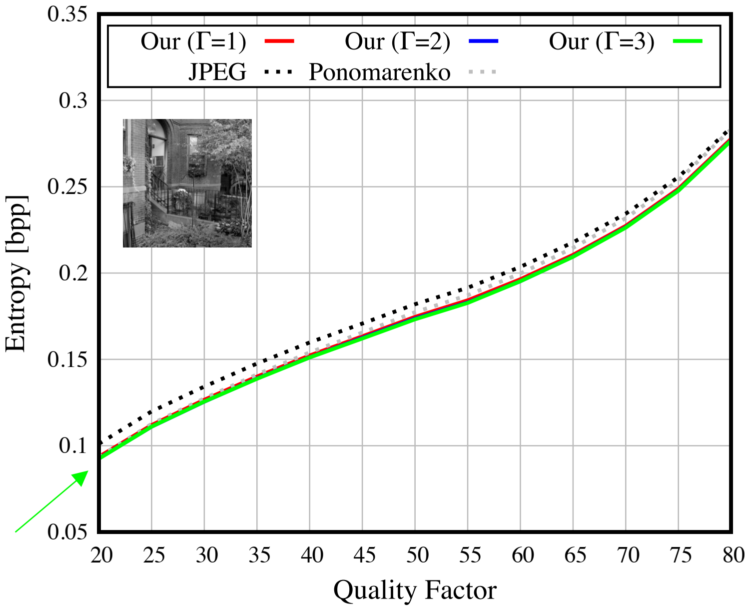
- Our method with $\Gamma = 1$ (num. cascading, red line) had a lower entropy.

Compared to the previous technique, our method with $\Gamma = 1$ had a lower entropy.

Experimental Results



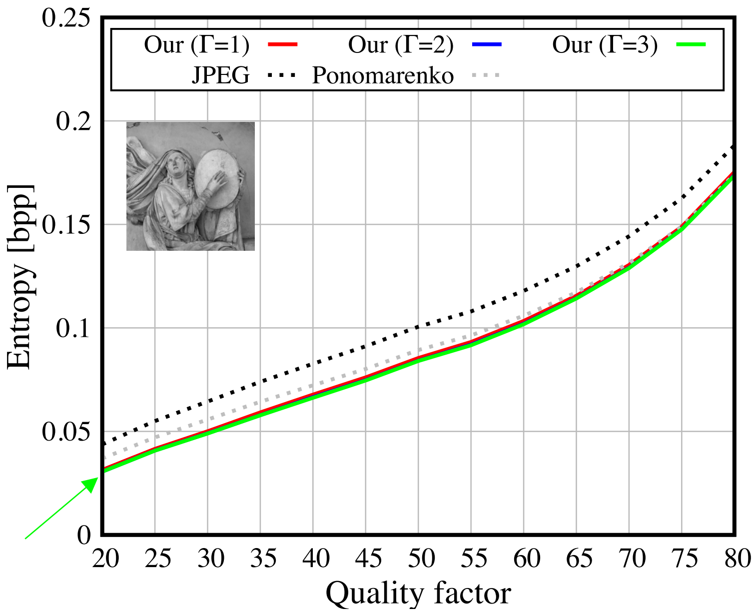


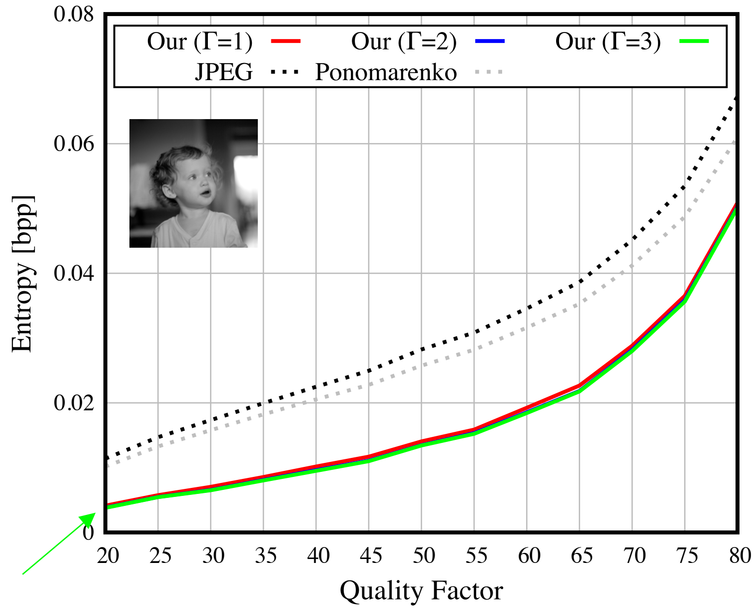


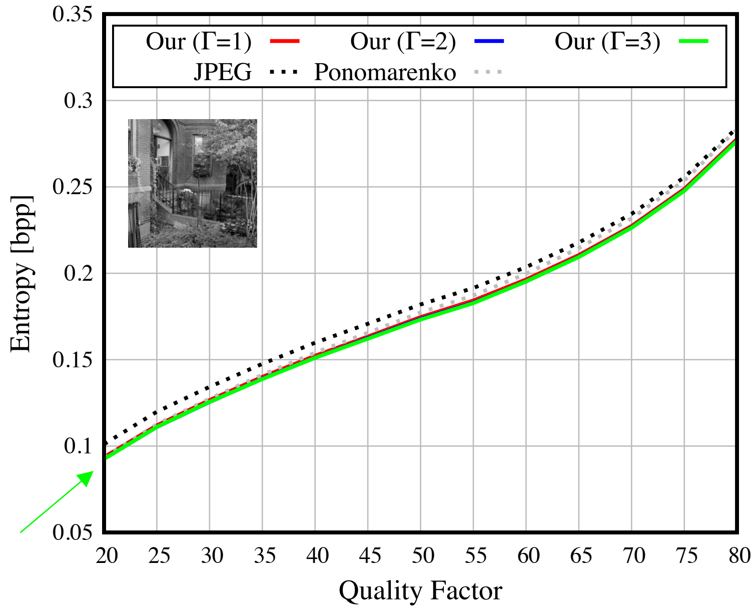
- Our method with $\Gamma = 1$ (num. cascading, red line) had a lower entropy.
- $\Gamma = 3$ (green line) gives lower entropy.

This result can be improved by increasing Γ,
which can be confirmed from green lines.

Experimental Results



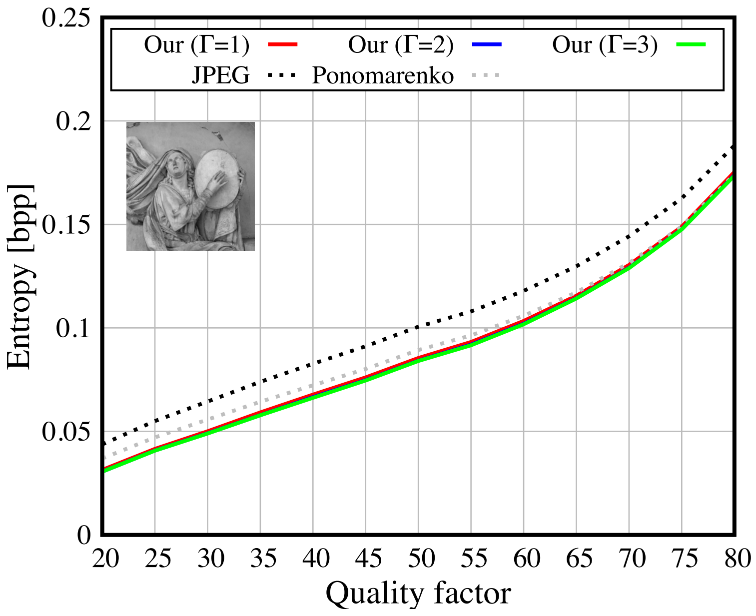


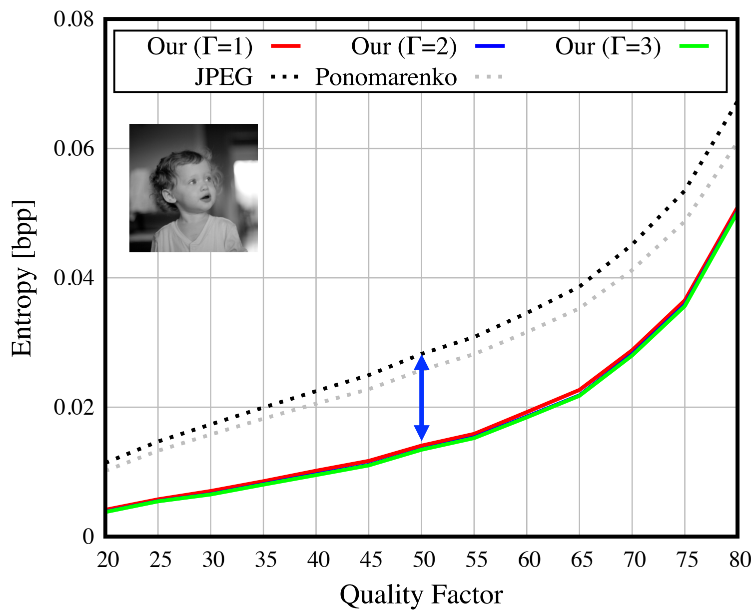


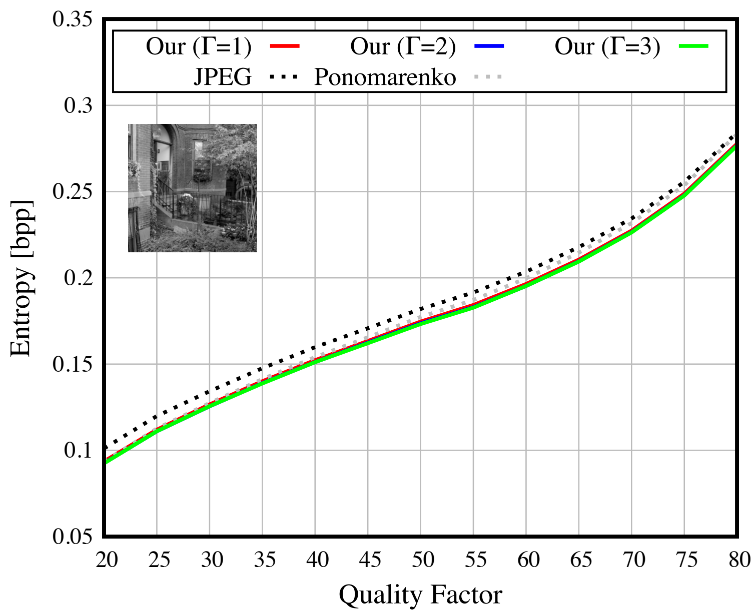
- Our method with $\Gamma = 1$ (num. cascading, red line) had a lower entropy.
- $\Gamma = 3$ (green line) gives lower entropy. → cascading is effective.

Thus, the cascading is effective for our method.

Experimental Results



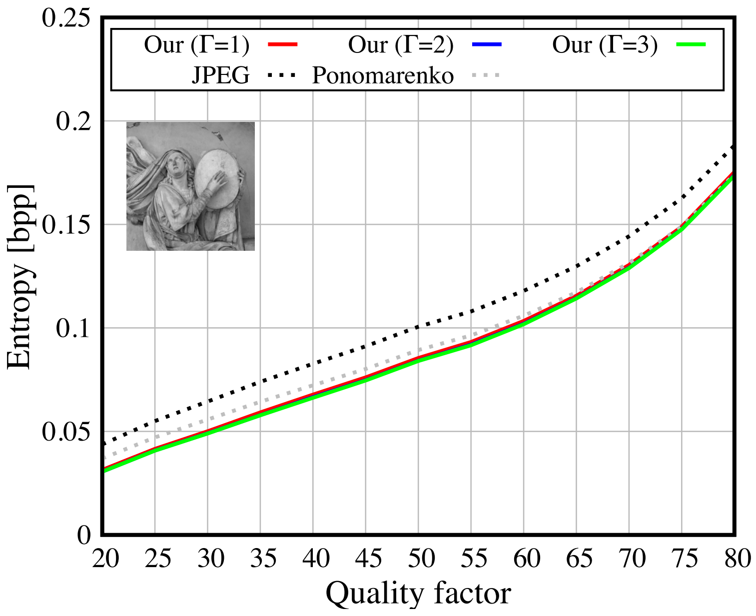


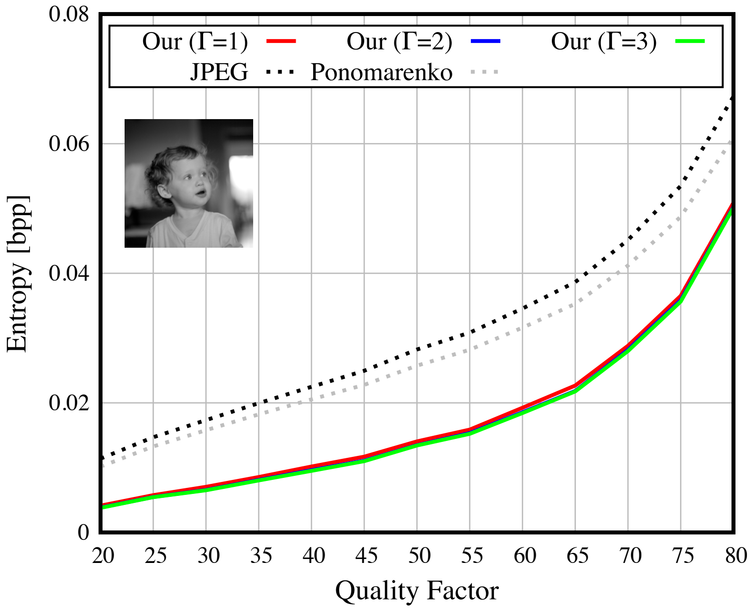


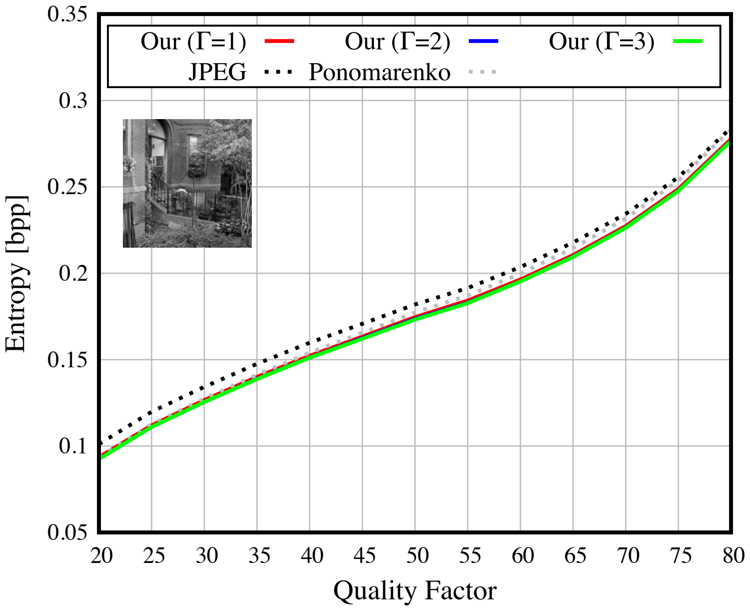
- Our method with $\Gamma = 1$ had a lower entropy.
- $\Gamma = 3$ (green line) gives lower entropy. → cascading is effective.
- Achieves half entropy

In the center result at QF = 50, our entropy is half of entropies in JPEG and Penomarenko et al., which is illustrated by the blue arrow.

Experimental Results





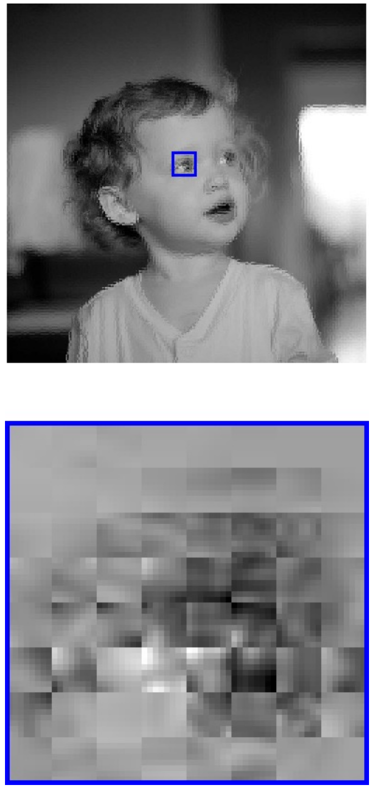


- Our method with $\Gamma = 1$ had a lower entropy.
- $\Gamma = 3$ (green line) gives lower entropy. → cascading is effective.
- Achieves half entropy

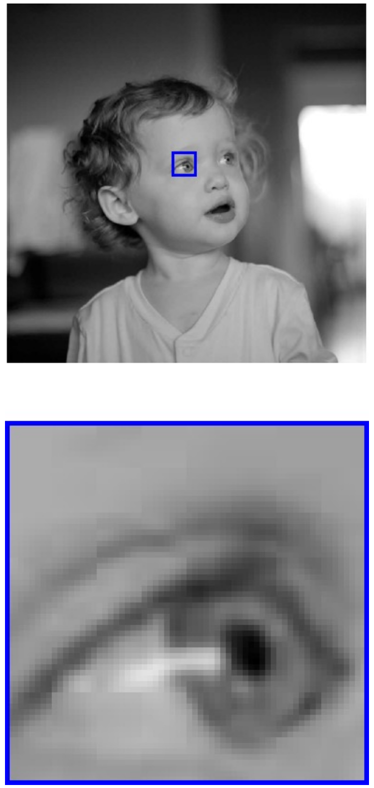
These results indicate that our method is so effective for compressing the sign information.

Experimental Results

(a) JPEG



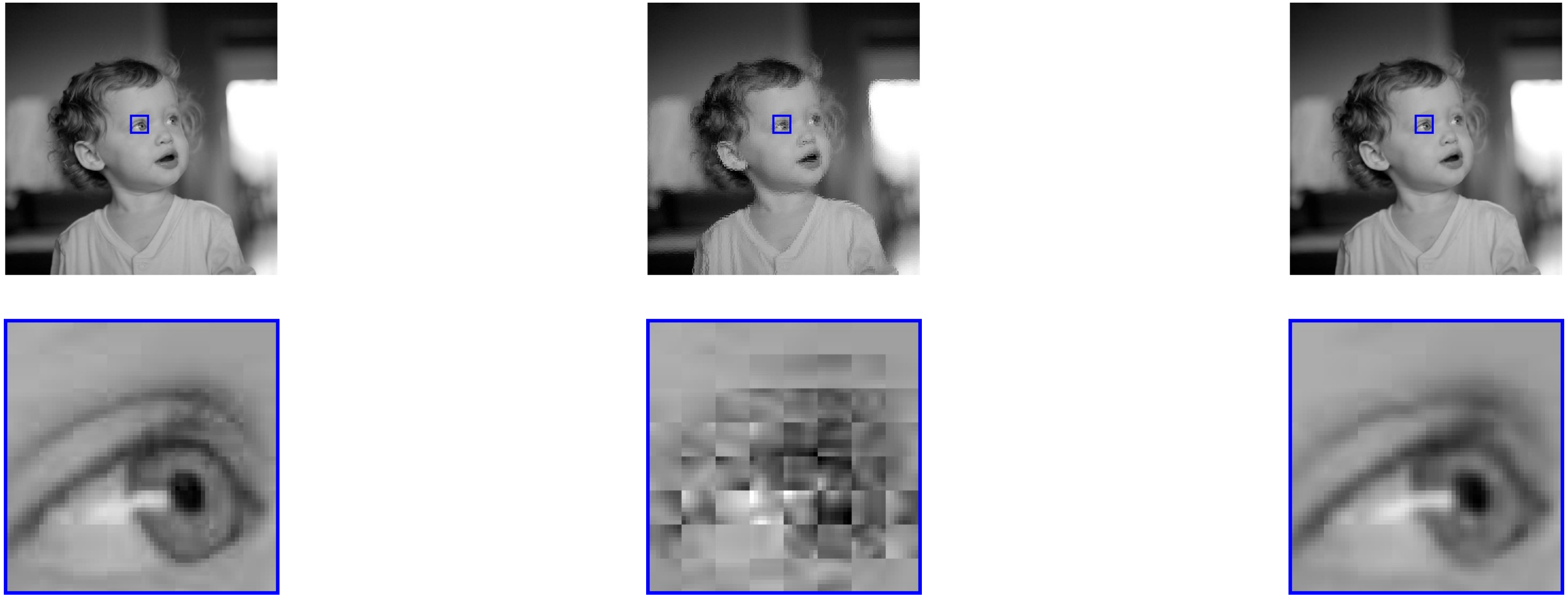
(b) Random signs



(c) Reconstructed

These images are examples of reconstructed images,
where (a) is a JPEG image and

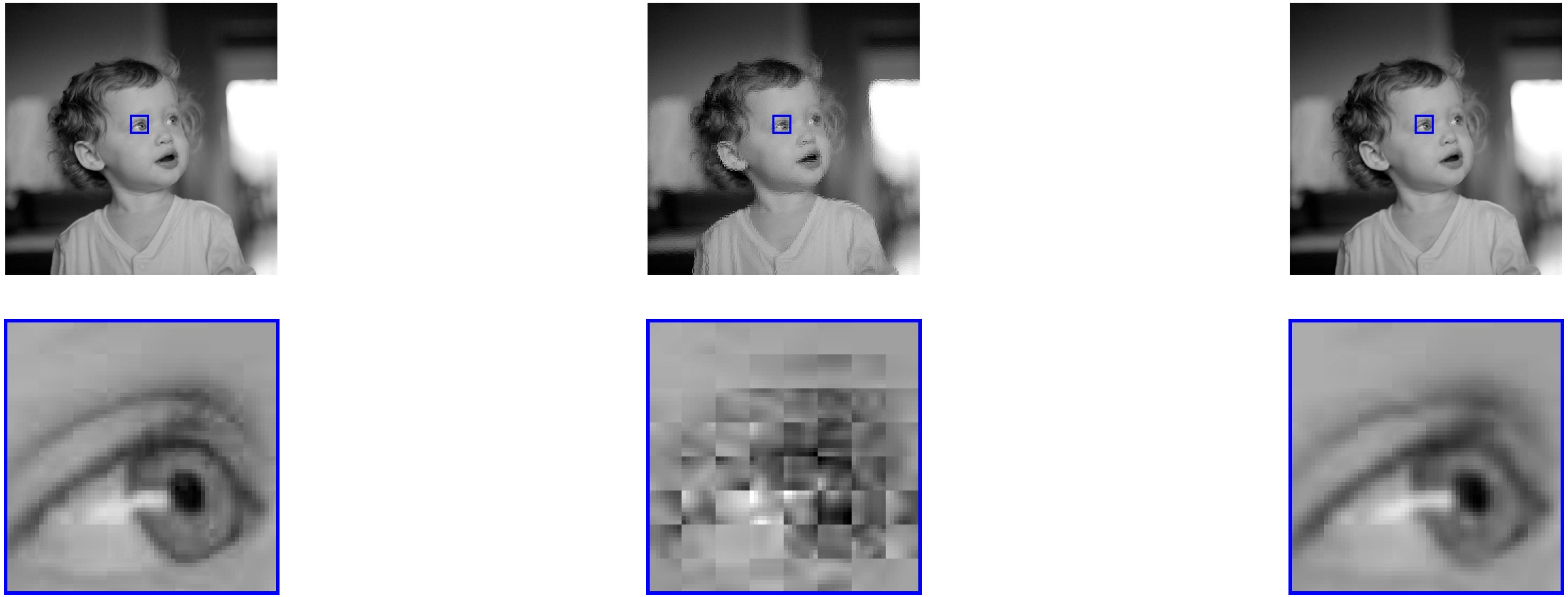
Experimental Results



(a) JPEG (b) Random signs (c) Reconstructed

(b) and (c) are reconstructed images using random sign bits and those retrieved by our method.

Experimental Results



(a) JPEG

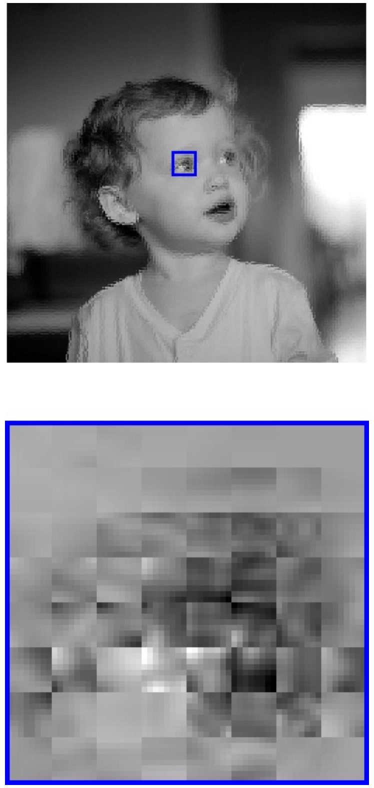
(b) Random signs

(c) Reconstructed

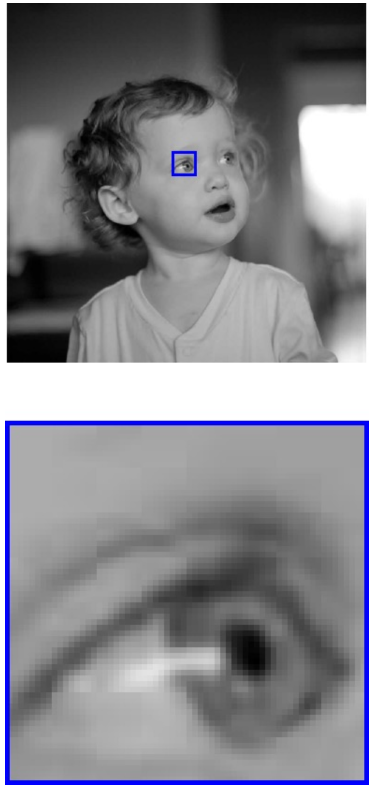
While (b) was completely degraded, (c) was very close to (a).

Experimental Results

(a) JPEG



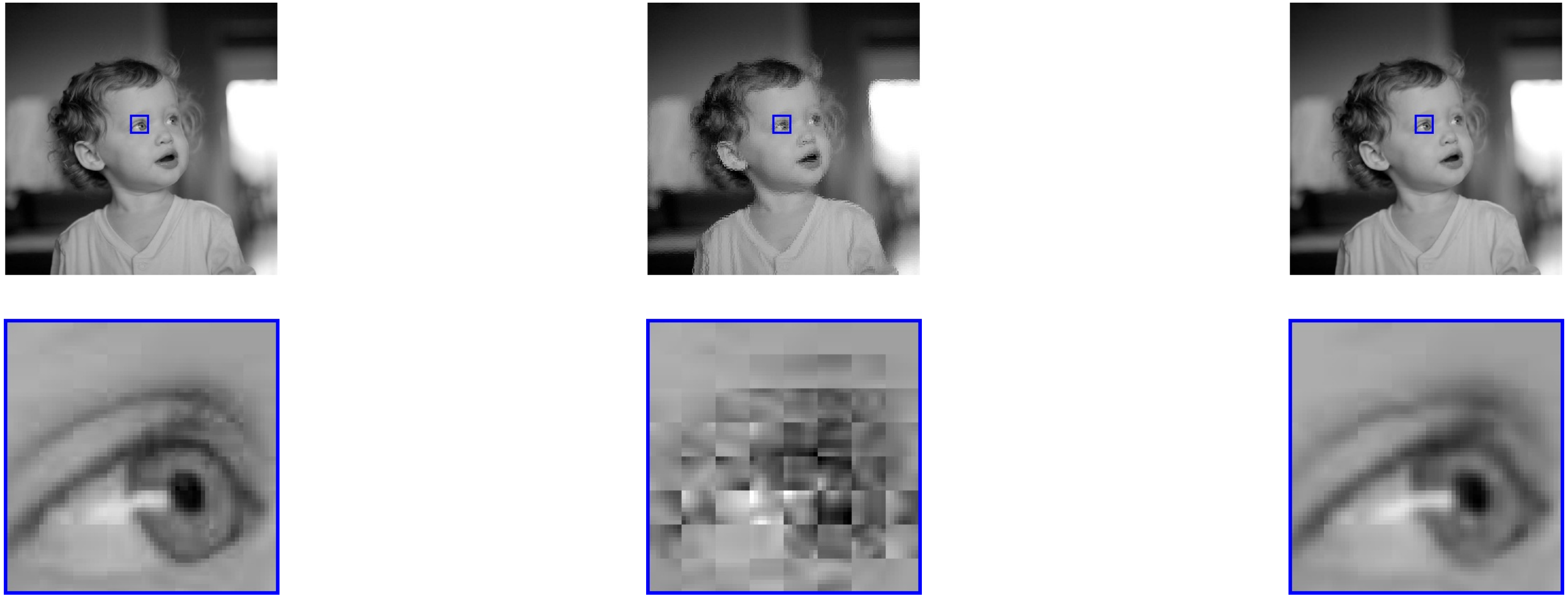
(b) Random signs



(c) Reconstructed

This result indicates that most of the sign bits were correctly retrieved, and

Experimental Results



(a) JPEG (b) Random signs (c) Reconstructed

residual bits consisted of many zeros and few ones,
resulting in small entropy values for the sign information.

Agenda

1. Introduction
2. Proposed Method
   2.1. Encoder and Decoder
   2.2. Sign Retrieval and Its Solution
3. Experimental Results
4. Conclusion

We finally summarize our study.

Conclusion

- Addressed an intractable sign compression problem based on phase retrieval
- Formulated phase-retrieval-based non-convex optimization problem, i.e., sign retrieval.
- Formulated its convex relaxation, i.e., regularized SignMax
- Cascaded Fienup method

  → Advantageous over previous technique.

In this study, we addressed an intractable sign compression problem based on phase retrieval.

Conclusion

- Addressed an intractable sign compression problem based on phase retrieval
- Formulated phase-retrieval-based non-convex optimization problem, i.e., sign retrieval.
- Formulated its convex relaxation, i.e., regularized SignMax
- Cascaded Fienup method

  → Advantageous over previous technique.

We first formulated a phase-retrieval-based non-convex problem, which we call sign retrieval.

Conclusion

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- Formulated phase-retrieval-based non-convex optimization problem, i.e., sign retrieval.
- Formulated its convex relaxation, i.e., regularized SignMax
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  → Advantageous over previous technique.

We then formulated a convex relaxation of the sign retrieval, that is the regularized SignMax.

Conclusion

- Addressed an intractable sign compression problem based on phase retrieval
- Formulated phase-retrieval-based non-convex optimization problem, i.e., sign retrieval.
- Formulated its convex relaxation, i.e., regularized SignMax
- Cascaded Fienup method

  → Advantageous over previous technique.

We finally proposed the cascaded Fienup method to efficiently solve the the regularized SignMax.

Conclusion

- Addressed an intractable sign compression problem based on phase retrieval
- Formulated phase-retrieval-based non-convex optimization problem, i.e., sign retrieval.
- Formulated its convex relaxation, i.e., regularized SignMax
- Cascaded Fienup method

→ Advantageous over previous technique.

These method give the high compression performance over previous techniques.

Conclusion

- Addressed an intractable sign compression problem based on phase retrieval
- Formulated phase-retrieval-based non-convex optimization problem, i.e., sign retrieval.
- Formulated its convex relaxation, i.e., regularized SignMax
- Cascaded Fienup method

  → Advantageous over previous technique.

This is all for my presentation. Thank you for your attention.