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Abstract

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High-Quality Soft Image Delivery with Deep Image Denoising

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***Abstract*—Soft image delivery uses pseudo-analog modulation for wireless image transmissions to prevent cliff and leveling effects subject to channel quality fluctuation and to realize graceful quality improvement according to wireless channel quality. Despite its attractive feature of graceful performance, the conventional soft image delivery suffers from low image quality when the analog-modulated symbols are severely impaired by fading and strong channel noise. In this paper, we propose a novel scheme of soft image delivery to reconstruct high-quality images from its low-quality observations. Specifically, the proposed scheme integrates deep convolutional neural network (DCNN)-based image restoration, i.e., deep image prior, into soft image delivery. The deep image prior learns a mapping function from the noisy image to the clean image based on user's perception-aware loss function using multiple training images in prior to soft delivery. The mapping function can restore a clean image even when the received image is distorted by strong fading and additive noise. From the evaluation results, the proposed scheme can remove fading and noise effects from the received images by using DCNN-based image restoration. For example, the proposed scheme achieves up to 0.44 improvement compared with the conventional soft image delivery in terms of structural similarity (SSIM) index at a deep fading channel.**

I. Introduction

Video streaming is one of the major applications in the wireless environment – according to Cisco visual networking index studies, nearly four-fifths (82%) of the world's mobile data traffic will be video contents by 2022 [1]. In conventional video streaming, they use the digital video compression and digital wireless transmission for video frames, i.e., images, in sequence [2]–[4]. For example, the video compression part uses H.264/Advanced Video Coding (AVC) [5] or H.265/High-Efficiency Video Coding (HEVC) [6] standards to generate a compressed bit stream using quantization and entropy coding. The wireless transmission part uses channel coding and a digital modulation scheme to reliably transmit the encoded bit stream.

However, such conventional digital-based schemes [7] have the following problems due to the unstable wireless channel. First, the encoded bit stream is highly vulnerable to bit errors. When the channel's signal-to-noise ratio (SNR) falls under a certain threshold, the received image quality drops significantly. This phenomenon is referred to as the cliff effect [8]. Second, the image quality does not gracefully improve even when the wireless channel quality is improved. This is known the leveling effect. Finally, quantization is a lossy process, whose distortion cannot be recovered at the receiver.

Soft transmission schemes [9]–[12] have been proposed to realize graceful image quality improvement with the improvement of wireless channel quality. Specifically, a sender directly transmits linearly-transformed image signals over a lossy channel and allocates power to the signals to maximize the received image quality, instead of using digital compression and digital modulation. In contrast to the conventional digital scheme, the image quality of the soft transmission schemes can be gracefully improved according to the wireless channel quality. Although the soft transmission schemes prevent the cliff effect due to the variation of wireless channel quality, the image quality of the conventional soft transmission schemes can be considerably low at deep fading channels.

To reconstruct high-quality images from noisy images, one of the typical methods is to solve the image denoising problem [13]–[15] between the sender and receiver. Specifically, the image denoising problem can be expressed as $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{n}$ where $\boldsymbol{x}$ and $\boldsymbol{y}$ denote the original and noisy images, and $\boldsymbol{n}$ is an additive noise. Here, the image denoising is a challenging ill-posed inverse problem. For solving image denoising problem, some learning-based image denoising methods [16], [17] have been proposed in recent years. The learning-based denoising methods train the weights of a mapping function to reconstruct the missing high-frequency/pixel details from the noisy images. Especially, deep convolution neural network (DCNN) [17]–[20] has been successfully applied to image denoising. DCNN first learns the weights of the mapping function using the noisy and original images based on massive number of typical image datasets. The learned DCNN model is used at the receiver to restore the missing high-frequency/pixel details from the noisy images. Since the mapping function can represent linear/nonlinear additive noise, the DCNN-based image denoising offers better reconstruction quality than conventional image denoising.

The main objectives of our study are three-fold: 1) to prevent cliff effect, 2) to gracefully improve image quality with the improvement of wireless channel quality, and 3) to reconstruct high-quality images from soft delivered noisy images over low-quality wireless channels. We propose a novel soft image delivery to overcome the issues of conventional schemes. To reconstruct high-quality images from its low-quality observations due to strong fading and channel noise, the proposed scheme integrates DCNN-based image denoising, specifically, recently proposed deep image prior (DIP) [20], into soft image delivery. The DIP consists of convolutional

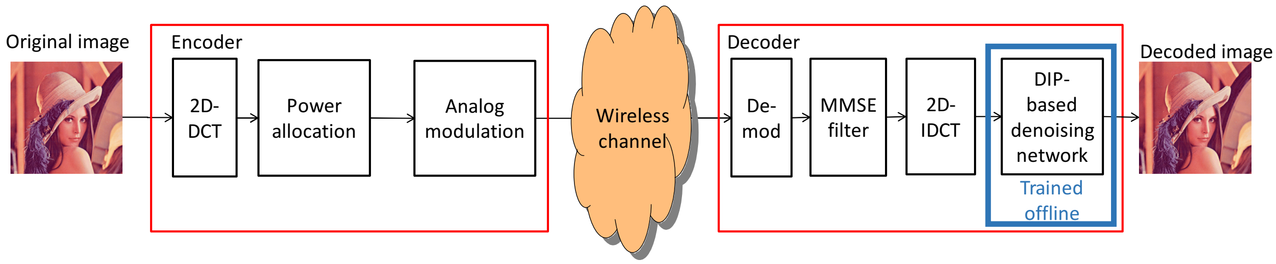


Fig. 1. Overview of the proposed soft image delivery, employing DIP-based image denoising.

networks to find linear/nonlinear noise effects for reconstructing clean images from the noisy images. For high-quality image reconstructions, the proposed scheme learns the weights of the networks based on loss gradients obtained from the original and soft delivered noisy images, whose datasets were synthetically generated from channel simulations offline. The trained DCNN weights are later used by the receiver to remove fading and noise effects from newly delivered soft images.

From evaluation results, the proposed scheme yields significantly better image quality than the conventional schemes of soft image delivery in fading and low-quality wireless channels by restoring image details through the use of the DIP-based image denoising. For example, the proposed scheme achieves up to 0.44 quality improvement in terms of structural similarity (SSIM) index [21] compared with the conventional scheme of soft image delivery, namely, SoftCast [9].

To the best of our knowledge, our study is the first study on the reduction of the fading and noise effects in wireless image delivery. Although recent studies [22]–[24] adopt DIP for image restoration in the different applications, they do not clarify the denoising performance in highly-distorted soft image delivery via Rayleigh fading channels.

Our contribution is three-fold: 1) we verify that the DIP-based denoising can raise the baseline image quality by restoring missing pixel details in soft delivered images, 2) we clarify an impact of loss functions in DIP-based image denoising on the reconstructed image quality, and 3) we demonstrate that Rayleigh fading effects [25] in addition to additive noise can be efficiently reduced by using the proposed decoding operations.

II. Soft Image Delivery with Deep Image Prior-based Image Denoising

The purposes of our proposed scheme are 1) to prevent cliff effect, 2) to achieve image quality that gracefully improves according to the wireless channel quality, and 3) to restore high-quality images from soft delivered images over fading and low-quality wireless channels. Fig. 1 shows the schematic of our proposed scheme. The encoder first performs a two-dimensional (2D) discrete-cosine transform (DCT) operation on the original images. The DCT coefficients are then scaled and analog-modulated according to the power of the DCT coefficients. Finally, the encoder sends the analog-modulated symbols to the receiver without extra digital encoding and modulations over a Rayleigh fading wireless channel with additive white Gaussian noise (AWGN).

At the receiver side, the decoder uses minimum mean-square error (MMSE) filter for frequency-domain denoising. The DCT coefficients are obtained from the received analog-modulated symbols through the use of MMSE filtering. Based on the reconstructed DCT coefficients, the receiver takes the inverse 2D-DCT operation to reconstruct the corresponding images. Finally, the receiver uses the DIP-based image denoising to further refine the image details from the reconstructed images. The DCNN weights in DIP denoiser are trained beforehand based on synthetic datasets generated through offline Monte–Carlo simulations to analyze linear and non-linear distortions of the soft image delivery scheme in pseudo wireless fading channels.

A. Encoder

The encoder first preforms 2D-DCT operation on the original image to obtain the DCT coefficients. In the proposed scheme, the encoder takes 2D-DCT for whole image. The DCT coefficients are mapped to I (in-phase) and Q (quadrature) components after the following power allocation.

Let x_i denote the ith analog-modulated symbol. Each analog-modulated symbol is scaled by g_i for noise reduction:

$$x_i = g_i \cdot s_i. \tag{1}$$

Here, s_i is the ith DCT coefficient and g_i is the scale factor which determines the coefficient's power allocation. The transmitter performs optimal power control by selecting g_i to achieve the highest image quality. Specifically, the best g_i is obtained by minimizing the mean-square error (MSE) under the power constraint with total power budget P as follows:

$$\min \quad \mathsf{MSE} = \mathbb{E}\left[(x_i - \hat{x}_i)^2\right] = \sum_i^N \frac{\sigma^2 \lambda_i}{g_i^2 \lambda_i + \sigma^2}, \tag{2}$$

$$\text{s.t.} \quad \frac{1}{N} \sum_i^N g_i^2 \lambda_i = P, \tag{3}$$

where $\mathbb{E}[\cdot]$ denotes expectation, $\hat{x}_i$ is an estimate of the transmitted symbol, λ_i is the power of ith DCT coefficient, N is the number of DCT coefficients, and σ^2 is a receiver noise variance. The near-optimal solution is expressed as [9]

$$g_i = \lambda_i^{-1/4} \sqrt{\frac{P}{\sum_j \sqrt{\lambda_j}}}. \tag{4}$$

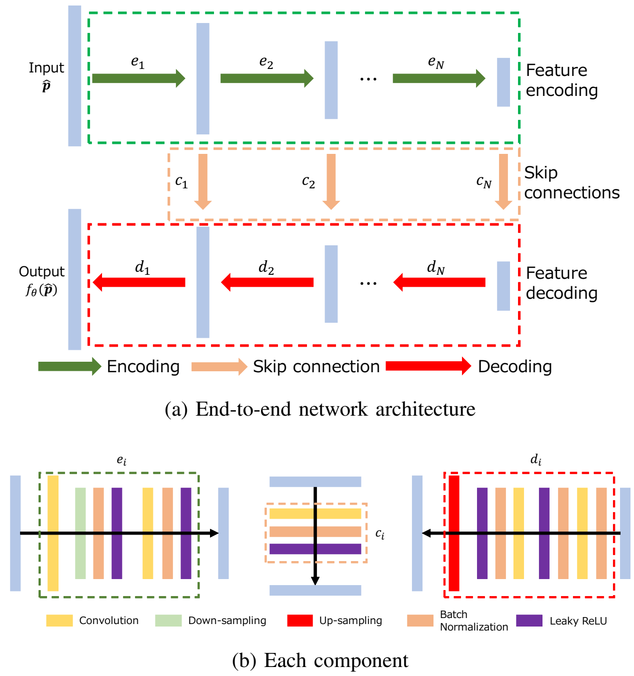


Fig. 2. DIP-based image denoiser.

B. Decoder

After transmission over the wireless channel, each symbol at the receiver can be modeled as follows:

$$y_i = h_i x_i + n_i, \tag{5}$$

where y_i is the ith received symbol, h_i is the channel gain, and n_i is an effective noise having a variance of σ^2. The receiver extracts DCT coefficients from I and Q components, and reconstructs the coefficients using MMSE filter [9] as follows:

$$\hat{s}_i = \frac{h_i g_i \lambda_i}{h_i^2 g_i^2 \lambda_i + \sigma^2} \cdot y_i. \tag{6}$$

The decoder then obtains reconstructed image by taking the inverse 2D-DCT for the filter output $\hat{s}_i$.

C. DIP-based Image Denoising

1) Neural Network Architecture: The DIP-based image denoiser [20] in the proposed scheme consists of convolutional neural networks with skip connections as shown in Fig. 2, where the noisy image $\hat{p}_i \in \mathbb{R}^{3\times W\times H}$ is fed into the denoiser to generate the denoised output $f_\theta(\hat{p}_i) \in \mathbb{R}^{3\times W\times H}$ with θ being the weights of the denoising networks. The DIP networks have three functionalities: feature encoding, skip-connections, and feature decoding.

The feature encoding can be divided into two parts: the first part contains convolution, down-sampling, batch normalization, and leaky rectified linear unit (ReLU) layers while the second part contains convolution, batch normalization, and leaky ReLU layers. The convolutional layers reduce the spatial resolution of the feature maps. For the down-sampling, we use the striding function implemented within convolution modules. The batch normalization standardizes the input values to balance the values in order to reduce the effect of outliers. The leaky ReLU is used for tuning the nonlinearity.

The skip connection is used to propagate the loss gradients from the output to the input to quickly reach the optimal allocation of all the network weights likewise residual networks. Specifically, this part uses convolution, batch normalization, and leaky ReLU layers to predict residuals, which has be verified to be more robust.

The feature decoding has two parts: the first part contains batch normalization, convolution, batch normalization, and leaky ReLU layers while the second part has batch normalization, convolution, and leaky ReLU layers. Finally, the decoding part takes up-sampling operation based on the bilinear upsampling to increase the spatial resolution for image reconstruction.

2) Weight Learning: The denoising networks can mitigate the distortion due to channel fading and additive noise from soft delivered images based on the weights between the network components. In this case, the denoising performance of the networks depends on the weights. To learn better weights for high-quality denoising, noisy image datasets are generated offline via Monte–Carlo simulations. Specifically, all potential distortions due to channel fading, additive noise, 2D-DCT, and MMSE filter are synthetically analyzed by DIP-based denoiser in off-line learning phase. Here, we consider various different wireless channel SNRs. By using synthetic datasets for the pairs of original and distorted images at specific channel models, the proposed scheme can learn better network weights depending on wireless channel quality. For stochastic gradient optimization, the proposed scheme uses two types of loss functions, MSE or SSIM:

$$l_{\mathrm{MSE}} = \left\| f_\theta(\hat{p}_i) - p_i \right\|_2^2,\ l_{\mathrm{SSIM}} = \mathrm{ssim}\big(f_\theta(\hat{p}_i), p_i\big), \tag{7}$$

where p_i denotes the i-th pair of original image patch and $f_\theta(\hat{p}_i)$ denotes the denoised image patch obtained from the DIP-based image denoiser with weight set θ. It is known that the SSIM metric [21] is more relevant for perceptual image quality than the MSE metric. By training the network weights θ using the loss function of MSE or SSIM [26], the proposed scheme can reconstruct clean images even when the soft delivered images are distorted by channel fading and additive noises. We note that the proposed scheme uses adaptive momentum (ADAM) optimizer [27] for weight learning in DIP-based denoising network.

III. Performance Evaluation

A. Simulation Settings

Metric: We evaluate the performance of reference schemes in terms of the peak SNR (PSNR) and SSIM [21]. PSNR is defined as follows:

$$\mathsf{PSNR} = 10 \log_{10} \frac{(2^L - 1)^2}{\varepsilon_{\mathrm{MSE}}}, \tag{8}$$

where L is the number of bits used to encode pixel luminance (typically eight bits), and $\varepsilon_{\mathrm{MSE}}$ is the MSE between all pixels

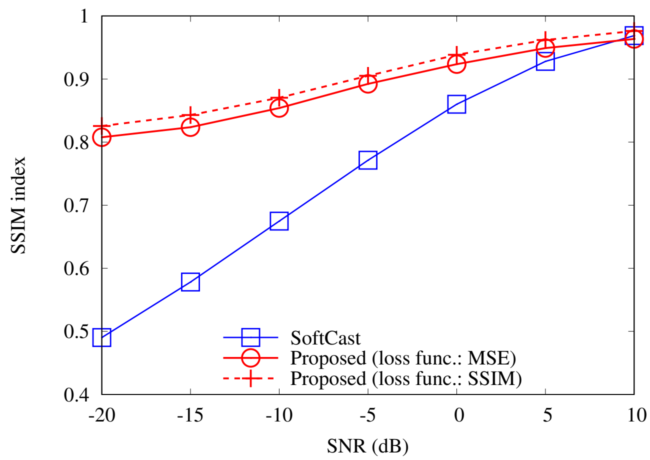


Fig. 3. SSIM performance of the proposed and conventional soft delivery schemes over AWGN channels as a function of channel SNRs.

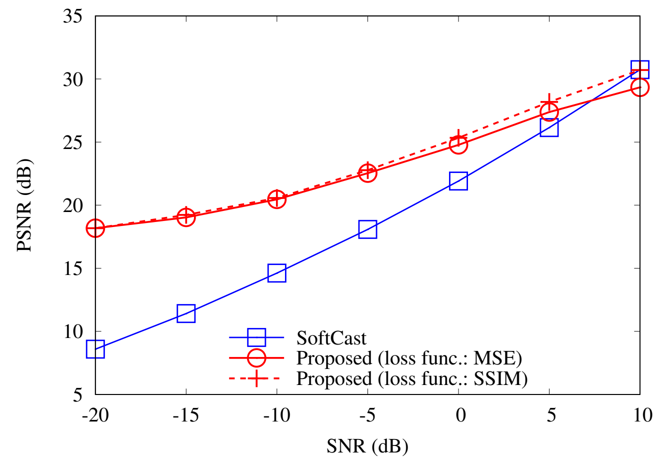


Fig. 4. PSNR performance of the proposed and conventional soft delivery schemes over AWGN channels as a function of channel SNRs.

of the decoded and the original images. SSIM can predict the perceived quality of image delivery. Larger values of SSIM close to 1 indicates higher perceptual similarity between original and decoded images.

Test Images: We used the benchmark dataset, namely, CIFAR-100 [28] for evaluations. CIFAR-100 consists of multiple training images and testing images. The training images are used for learning the network weights while the testing images are used for comparison in terms of image and visual quality.

Wireless Channel Environment: We consider Rayleigh fading channels for realistic wireless environments in addition to AWGN channels. In Rayleigh fading channels, the channel gain h_i follows the complex Gaussian distribution, i.e., $h_i \sim \mathcal{CN}(0, 1)$, where $\sim$ means "distributed as" and $\mathcal{CN}(a, b)$ is a complex Gaussian distribution with a mean of a and a variance of b. On the other hand, an additive noise in both Rayleigh fading and AWGN channels n_i follows white Gaussian distribution with a variance of σ^2, i.e., $n_i \sim \mathcal{CN}(0, \sigma^2)$.

B. Image Quality in AWGN Channels

We first evaluate the image quality of reference schemes in AWGN channels to clarify the baseline performance of the proposed decoding operations. Figs. 3 and 4 show the image quality of the proposed schemes with loss functions and conventional scheme of soft image delivery, namely, SoftCast [9], over AWGN channels as a function of wireless channel SNRs. SoftCast directly maps linear-transformed 2D-DCT coefficients on the I and Q components for image delivery to prevent cliff effect and gracefully improve image quality according to wireless channel quality. From the evaluation results, we can observe the following key points:

- The proposed schemes realize graceful quality improvement with the improvement of wireless channel quality and yield better image quality compared with the conventional SoftCast irrespective of the loss functions.
- Although the conventional SoftCast suffers from low image quality in low channel SNR regimes due to a strong channel noise, the proposed scheme achieves better image quality by denoising an effective distortion from the soft delivered images using DIP-based denoiser.
- A loss function of SSIM offers better denoising performance in the proposed scheme in terms of both image quality metrics of PSNR and SSIM.

For example, the proposed scheme with a loss function of SSIM achieves quality improvement by 0.15 on average in terms of SSIM over the conventional SoftCast across wireless channel SNRs of -20 to 10 dB. The quality improvement is much more significant at low channel SNRs, e.g., greater than 0.3 improvement in SSIM index is observed at an SNR of -20 dB.

To discuss reconstructed visual quality of each reference scheme in AWGN channels, Figs. 5 (a) through (g) show snapshots at different wireless channel SNRs. In Figs. 5(b) and (e), the reconstructed images are severely distorted even after an optimized MMSE filter. On the other hand, the proposed scheme with a loss function of SSIM in Figs. 5(d) and (g) can effectively remove a channel noise from the images in Figs. 5(b) and (e) by using DIP-based denoising at the decoder irrespective of wireless channel SNRs. In addition, we can see the proposed scheme with a loss function of SSIM can reconstruct high-quality images, i.e., similar color images, in comparison to the denoising scheme trained with a loss function of MSE.

C. Image Quality in Rayleigh Fading Channels

We demonstrated DIP-based image denoising in the proposed scheme can realize graceful and better image quality in soft image delivery over AWGN channels. In this section, we discuss the performance of the proposed scheme in more realistic wireless channels, i.e., Rayleigh fading channels.

Figs. 6 and 7 show the image quality of the proposed and conventional soft delivery schemes in terms of SSIM and PSNR, respectively, over Rayleigh fading channels as

(a) Original

(b) SoftCast
SNR: -10 dB
PSNR: 14.6 dB
SSIM: 0.675

(c) Proposed (MSE loss)
SNR: -10 dB
PSNR: 20.5 dB
SSIM: 0.854

(d) Proposed (SSIM loss)
SNR: -10 dB
PSNR: 20.6 dB
SSIM: 0.870

(e) SoftCast
SNR: 0 dB
PSNR: 21.9 dB
SSIM: 0.860

(f) Proposed (MSE loss)
SNR: 0 dB
PSNR: 24.8 dB
SSIM: 0.923

(g) Proposed (SSIM loss)
SNR: 0 dB
PSNR: 25.3 dB
SSIM: 0.938

Fig. 5. Snapshots of CIFAR-100 over AWGN channels at wireless SNRs of -10 dB and 0 dB.

a function of wireless channel SNRs. We can observe the following points from the evaluation results:

- Even in Rayleigh fading channels, both proposed schemes realize better image quality compared with the conventional SoftCast irrespective of the loss functions.
- An image quality of the conventional SoftCast is significantly low in low wireless SNR regimes due to channel gains and channel noises.
- In AWGN channels, the proposed scheme performs comparable to conventional SoftCast at a channel SNR of 10 dB. On the other hand, the proposed schemes keep much higher image quality than the conventional scheme in Rayleigh fading channels for wireless channel SNRs up to 30 dB.

In particular, the proposed scheme with a loss function of SSIM achieves quality improvement by 0.30 on average in terms of SSIM over the conventional SoftCast across wireless channel SNRs of -20 to 30 dB.

We demonstrate the visual quality over Rayleigh fading channels in Figs. 8 (a) through (g), which show snapshots at different wireless channel SNRs. We can see that the quality of the SoftCast images in Figs. 8(b) and (e) are highly distorted by channel fading and additive noise. Interestingly,

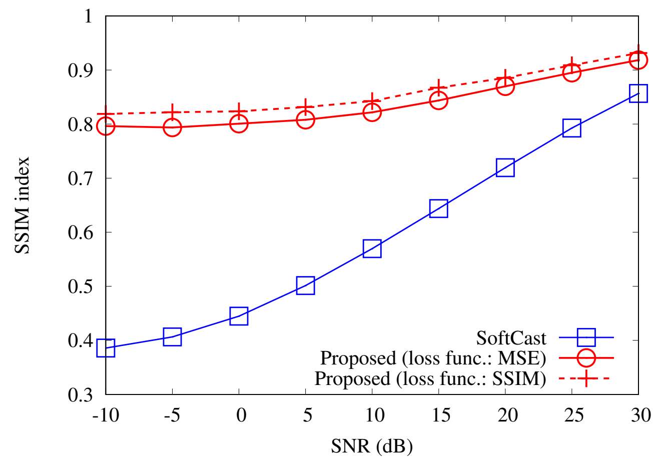


Fig. 6. SSIM performance of the proposed and conventional soft delivery schemes in Rayleigh fading channels as a function of wireless channel SNRs.

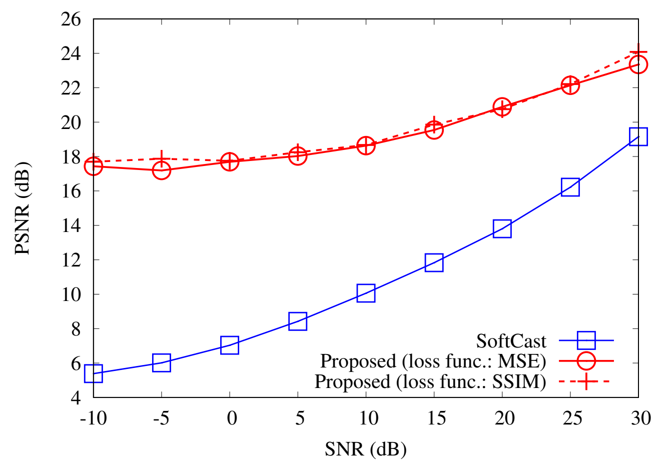


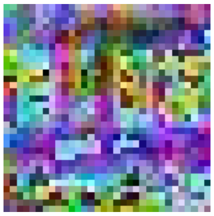
Fig. 7. PSNR performance of the proposed and conventional soft delivery schemes in Rayleigh fading channels as a function of wireless channel SNRs.

the proposed schemes can mitigate such effects by using deep image denoiser. It is verified that the image denoiser in the proposed scheme can realize high-quality soft image delivery over realistic wireless fading channels.

IV. Conclusions

We have proposed a novel scheme of soft image delivery to realize graceful and better image quality with the improvement of wireless channel quality. Specifically, the proposed scheme integrates DIP-based image denoiser into SoftCast to yield better image quality even in fading and low-quality wireless channels. The DIP-based image denoiser in the proposed scheme learns the weights of the denoising network in prior to soft image delivery to reconstruct high-quality images from soft delivered noisy images. Evaluation results demonstrated that the proposed scheme achieves higher image quality than the conventional scheme of soft image delivery by mitigating distortion due to channel fading and strong additive noises

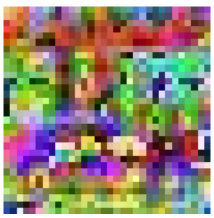
(a) Original



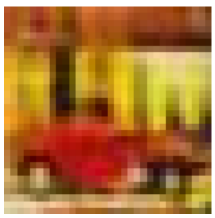
(b) SoftCast
SNR: -10 dB
PSNR: 5.1 dB
SSIM: 0.385

(c) Proposed (MSE loss)
SNR: -10 dB
PSNR: 17.4 dB
SSIM: 0.796

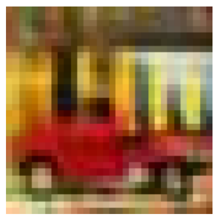
(d) Proposed (SSIM loss)
SNR: -10 dB
PSNR: 17.7 dB
SSIM: 0.819



(e) SoftCast
SNR: 10 dB
PSNR: 10.1 dB
SSIM: 0.570



(f) Proposed (MSE loss)
SNR: 10 dB
PSNR: 18.6 dB
SSIM: 0.822



(g) Proposed (SSIM loss)
SNR: 10 dB
PSNR: 18.7 dB
SSIM: 0.842

Fig. 8. Snapshot of CIFAR-100 over Rayleigh fading channels at SNRs of -10 dB and 10 dB.

through the use of DIP-based image denoising. For instance, the proposed scheme achieves SSIM improvement by 0.30 on average over the conventional SoftCast in Rayleigh fading channels under wireless channel SNRs of -20 to 30 dB.

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