Analog Images Communication Based on Block Compressive Sensing

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Abstract. Recently, owing to graceful performance degradation for various wireless channels, analog visual transmission has attracted considerable attention. The pioneering work about analog visual communication is SoftCast, and many advanced works are all based on the framework of SoftCast. In this paper, we propose a novel analog image communication system called CSCast based block compressive sensing. Firstly, we present the system framework and detailed design of CSCast, which consists of discrete wavelet transform, power scaling, compressive sampling and analog modulation. Furthermore, we discuss how to determine the appropriate value of scaling factor α in power allocation, and block size of measurement matrix in compressive sampling. Simulations show that the performance of CSCast better than Softcast in all SNR range, and better than Cactus in high SRN range. In particular, CSCast outperforms over Softcast about 1.72 dB. And CSCast achieves the maximum average PSNR gain 1.8 dB over Cacuts and 2.03 dB over SoftCast when SNR = 25 dB, respectively. In addition, our analyses shows CSCast can save about 75% overhead comparing to SoftCast and Cactus.

Keywords: Analog images communication · Block compressive sensing · Wireless image multicast

1 Introduction

Nowadays, digital image/video transmission technologies serve as an important role in modern wireless multimedia networks. However, these traditional transmissions methods of image/video include quantization and entropy coding, it lacks of scalability and robustness [1]. Especially, since traditional image/video transmission systems suffer high bit error, the received images/videos appear mosaic when the quality of channel below a certain threshold.

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Recently, analog visual transmission has attracted considerable attention owing to its graceful performance degradation for various wireless channels. Jakubczak et al. [1] firstly proposed a cross-layer analog visual communications system SoftCast. This pioneering work changes the network stack to act like a linear transform, and the conventional quantization and entropy coding are all skipped. SoftCast is very robust and efficient in unicast and multicast because it avoids the cliff effect in digital communications. Subsequently, a lot of research work based on softcast are emerged [2–8]. A lot of these work reconstruct images with the help of size information. This undoubtedly will increase the overhead of those communication system. Especially, Cui et al. [5] designed a visual transmission system named Cactus, which adopts temporal filtering at the sender and denoising techniques at the receiver to fully exploit the tempo-spatial redundancy. Cactus is the state of the art analog visual communication schemes without using side information.

Compressive sensing (CS) is a novel sampling theory that challenges the traditional data acquisition. It states that an n-dimensional signal $x \in R^n$ having a sparse or compressible representation can be reconstructed form m linear measurements even if $m < n$. A few work are on wireless visual communications based on CS [9–11]. These work use the entire image as input of CS encoder. To save memory storage and reduce computation time, references [12,13] introduce block compressive sensing (BCS) to implement wireless image transmission system.

However, the above work is either based on softCast framewok, or the performance needs to be improved. In this paper, we propose an another analog image communication framework named CSCast, based on block compressive sensing. CSCast consists of discrete wavelet transform, power scaling, compressive sampling and analog modulation. We adopt the Cohen Daubechies Feauveau 9/7 (CDF 9/7) wavelet transform [14] to de-correlating for input images signal. In power allocation, we set scaling factor $\alpha = -1/4$ to achieve good performance. And, we adopt block compressive sensing [15] to encode DWT coefficients, and use compressive reconstructed algorithm named CS-SPL-DCT [16,17] to decoding. Simulations show that the performance of CSCast better than Softcast in all SNR range, and better than Cactus in high SRN range. On test iamges, CSCast outperforms over Softcast about 1.72 dB. And CSCast achieves the maximum average PSNR gain 1.8 dB over Cacuts and 2.03 dB over SoftCast when SNR = 25 dB, respectively. Comparing to SoftCast and Cactus, CSCast can save 75% overhead.

The rest of this paper is organized as follows. Section 2 presents the proposed novel analog image communication system. The simulation evaluations of our proposed system are included in Sect. 3. Finally, Sect. 4 concludes this paper.

2 System Design

2.1 Overview of System Model

Figure 1 describes the system framework of CSCast. Transmitter of this system includes discrete wavelet transform (DWT), power allocation, compressive sampling, and analog modulation. Receiver performs contrary operators of

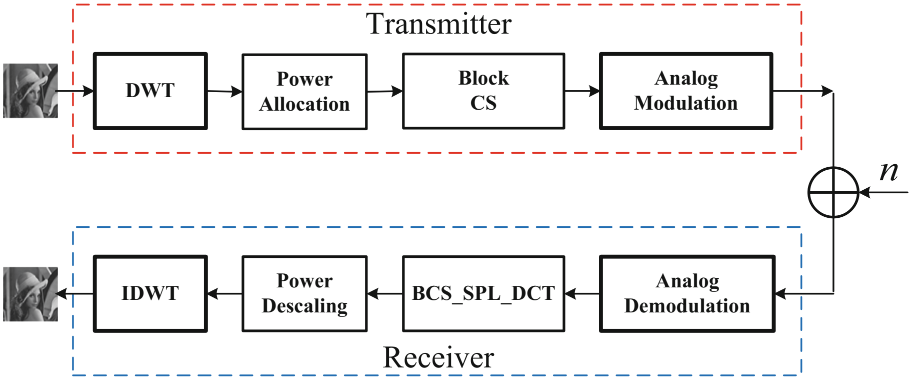

Fig. 1. System framework of CSCast.

transmitter, includes analog demodulation, compressive sensing decoding, power descaling and invert discrete wavelet transform (IDWT).

From the blocks diagram of CSCast, we can find that our proposed system is different from Softcast. In Softcast, 2-dimensional discrete cosine transform (DCT) and power scaling are performed in the transmitter, and power descaling and 2-dimensional discrete cosine invert transform (IDCT) transforming are performed in the receiver. It is should be note that power descaling in Softcast uses linear least squares estimator (LLSE) to estimate coefficients in receiver. In CSCast, power scaling and power descaling are only multiplied a factor corresponding to a block coefficients.

2.2 Transmitter

In transmitter of CSCast, to remove the spatial correlation in the original natural image, the original signal in pixel domain is converted to wavelet domain by discrete wavelet transform. This operator is similar to that used in JPEG2000 standard [18]. In this paper, we adopt the Cohen Daubechies Feauveau 9/7 (CDF 9/7) wavelet transform [14] to de-correlate for an input image, and set the decomposition layer number $L = 5$.

$$X_{dwt} = f_{dwt}\left(X, L\right). \tag{1}$$

where X is a input image, X_{dwt} is the discrete wavelet coefficients, its schematic diagram is described by Fig. 2. From the diagram, we can observe L subband coefficients, and the l-th subband includes three blocks, i.e., X_{Hl}, X_{Vl}, X_{Dl}. In L-th subband, there are four coefficients blocks X_{HL}, X_{VL}, X_{DL} and X_{AL}. Because of $L = 5$, we can get $N = 3L + 1 = 16$ coefficients blocks.

If we use analog modulation to send these discrete wavelet coefficients, the energy carried by each coefficient determines its anti-noise ability in wireless

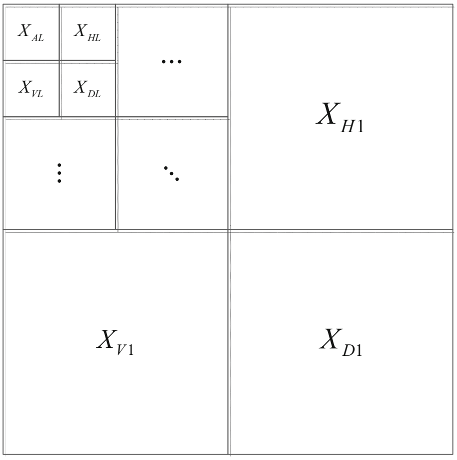

Fig. 2. Schematic diagram of wavelet coefficients.

channel. In other word, power allocation directly affects the quality of reconstructing image at the receiver. As Fig. 2, these wavelet coefficients are divided into N blocks, and the coefficient of power allocation in each block is calculated by

$$g_i = C \cdot \left(\sigma_i^2\right)^{\alpha}. \tag{2}$$

where $\sigma_i^2, i = 1, 2, ..., N$ is the variance information of i'th block, C is a constant number to ensure all allocated powers satisfy the constraint of total transmitting power, and α is a power scaling factor. According to the channel protection, a larger value of α can provides better protection for the low frequency band coefficients. On the contrary, smaller value of α provides protection for the high frequency band coefficients. So, we should choose the right value to make the system achieves better performance. Like Softcast, we also set $\alpha = -1/4$, and it can achieve the best performance. Section 3 gives the evaluation results of choosing different value of α. We can get the power allocated coefficients.

$$X_{pa} = G. * X_{dwt}. \tag{3}$$

where G is a power allocation matrix which consists of different sub-matrices, and the elements of each sub-matrix are all g_i, $.*$ is dot product operator in matrix.

Next, our proposed system performs compressive sampling. Consider the high computational load of full-signal compressed sensing, we adopt block-based compressed sensing (BCS) [15]. In BCS framework, X_{pa} is decomposed into non-overlapping blocks of $B \times B$ pixels, and each block is compressively sensed independently. Assume that the dimensions of the block sensing matrix Φ_B are $B^2R \times B^2$, and the measurement vector of i'th block is given by

$$X_{cs_i} = \Phi_B X_{B_i}. \tag{4}$$

where $X_{B_i} \in \mathbb{R}^{B^2}$ is the i'th coefficients block, and Φ_B is an orth-normalized independent identically distributed (i.i.d) Gaussian matrix.

Finally, our proposed system performs analog modulations. To save wireless resource, every two adjacent coefficients make up a complex symbol.

$$X_{am_k} = X_{cs_{(2k-1)}} + jX_{cs_{(2k)}}, k = 1, 2, ... \tag{5}$$

2.3 Receiver

Assume that the channel is additive white Gaussian noise (AWGN), the receiver receives signals $Y_n = X_{am} + \mathbf{n}$, where $\mathbf{n}$ is a complex vector whose entries are obey i.i.d. Gaussian distribution. The operators performed at receiver are as follows.

Firstly, receiver performs analog demodulations. The system separates the real and imaginary part from received complex signal, and we get Y_{am}.

Secondly, to improve the performance of reconstructed image, we use (BCS_SPL_DCT) [16,17] method to implement CS decoding. After this operator, we get the reconstructed blocks coefficients Y_{B_i}.

Thirdly, according to the g_i transmitted from sender, the system performs power de-scaling, i.e., $Y_{dwt_i} = Y_{B_i}/g_i$. It should be note that Softcast implements power descaling by using LLSE, while the power de-scaling in CSCast is done by multiplying a coefficient.

Finally, receiver performs the operator of reconstructing image by invert discrete wavelet transform.

$$\hat{X} = f_{idwt}(Y_{dwt}, -L). \tag{6}$$

3 Simulation Results

In this section, the performance of proposed scheme is evaluated by comparison with reference schemes. We develop and implement CSCast on a personal computer. This PC was equipped with an i7 CPU with 2.4 GHz and 16 GB DDR4 memory.

3.1 Evaluation Metric

In our evaluation, peak signal-to-noise ratio (PSNR) is used to assess image quality. PSNR is computed by

$$PSNR = 10log_{10}\frac{255^2}{MSE}, \tag{7}$$

where $MSE = \frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left(f\left(x,y\right) - \tilde{f}\left(x,y\right)\right)^2$. In addition, we set the SNR region from 5 to 25 dB.

Table 1. Performance comparison among different value of α.

α/SNR	5 dB	10 dB	15 dB	20 dB	25 dB
$\alpha = -1/8$	25.9418	30.8872	35.9572	40.9012	45.8202
$\alpha = -1/5$	27.9094	32.8866	37.8345	42.8075	47.8097
$\alpha = -1/4$	**28.1969**	**33.2814**	**38.1153**	**43.2551**	**48.1432**
$\alpha = -1/3$	27.0085	32.1548	37.0848	41.8705	46.6731

3.2 Parameters Selection

In this subsection, we first evaluate how much the size of sampling matrix Φ_B affects the performance of CSCast. Then, we give out how to choose the value of α to achieve better performance. The two problem are discussed as follows.

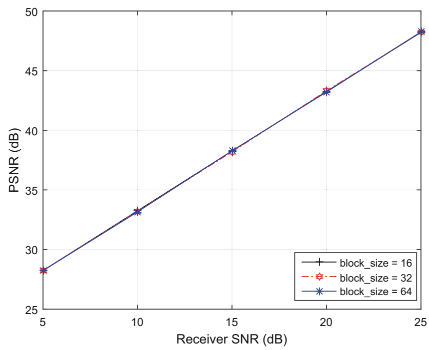

Fig. 3. PSNR comparison among different size of Φ.

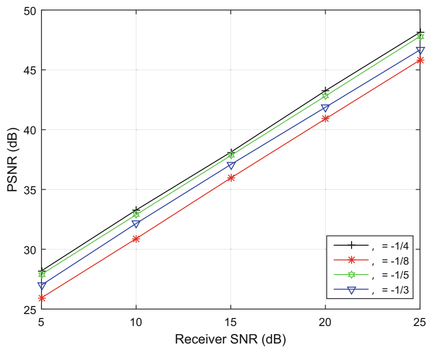

Fig. 4. PSNR comparison among different α.

How to set up the size of measurement matrix Φ_B? Given a fixed $\alpha = -1/4$, Fig. 3 shows the result of comparison among three size of Φ_B through simulation experiments. We can find that the size of Φ_B isn't affect the performance of CSCast. We know that the computation complexity will increase with the increasing of size of Φ_B. Therefore, we set the size of Φ_B equals 16×16.

How to choose the value of α? In simulation, we set $\alpha = \{-1/8, -1/5, -1/4, -1/3\}$, respectively. Figure 4 shows the PSNR comparison among these schemes, and Table 1 gives out the detailly PSNR value of different schemes in all SNR. we can observe that the system achieves the best performance when $\alpha = -1/4$.

3.3 Performance Comparison

(1) Reference Schemes

The first reference scheme is Softcast [1], which is the most typical joint source and channel coding based scheme. Softcast is pioneering work to act like linear transform, and skips the conventional quantization and entropy coding. In SoftCast, 2D-DCT transforming and power scaling are performed in the transmitter, and power descaling and 2D-IDCT transforming are performed in the receiver.

The second reference scheme is Cactus [5] based on Softcast. In the implemented Cactus, to utilize efficiently the BM3D algorithm [19], transmitter performs IDCT on the spatial data after power allocation, and receiver performs DCT on the denoising data after BM3D. Except operators in Softcast, Cactus needs additional IDCT, DCT, and BM3D operators.

(2) Performance Comparison

In this simulation, we choose *boat*, *lena*, *cameraman*, and *peppers* as test images. For fair comparison, we set the compression ratio $R = 1$ in experiments. Given a fixed image, all schemes transmit the same size of data.

Table 2. Performance comparison among reference schemes.

Images	Schemes	5 dB	10 dB	15 dB	20 dB	25 dB
Boat	CSCast	29.3029	34.3619	**39.4057**	**44.3888**	**49.3655**
	SoftCast	27.9161	32.8640	37.8047	42.7524	47.5299
	Cactus	**30.9983**	**34.5501**	38.1904	43.0946	47.6810
Cameraman	CSCast	26.3936	31.1772	36.1703	**41.1463**	**46.0907**
	SoftCast	25.0142	29.7584	34.7358	39.7218	44.5371
	Cactus	**29.4773**	**32.8349**	**36.5414**	40.2382	44.6729
Lena	CSCast	28.2160	33.1329	**38.2140**	**43.1397**	**48.1949**
	SoftCast	26.3322	31.3363	36.1510	41.0875	45.9312
	Cactus	**29.5158**	**33.2710**	37.0620	41.2568	46.4771
Peppers	CSCast	30.4984	**35.4353**	**40.3915**	**45.3343**	**50.3805**
	SoftCast	28.2635	33.1763	38.1407	43.2035	47.8751
	Cactus	**31.5800**	34.9598	38.5314	43.4345	47.9992

Table 2 gives out the PSNR performance comparison among different schemes on test images. The bold numbers are the best performance of test images at a SNR. We can observe that CSCast achieves better performance over Softcast in all SNR range, and achieves better performance over Cactus in high SNR range.

Based on Table 2, we calculate the average PSNR for every scheme. Figure 5 shows the PSNR performance comparison results. From Fig. 5, we can observe that the performance of CSCast and Cactus better than Softcast. With the

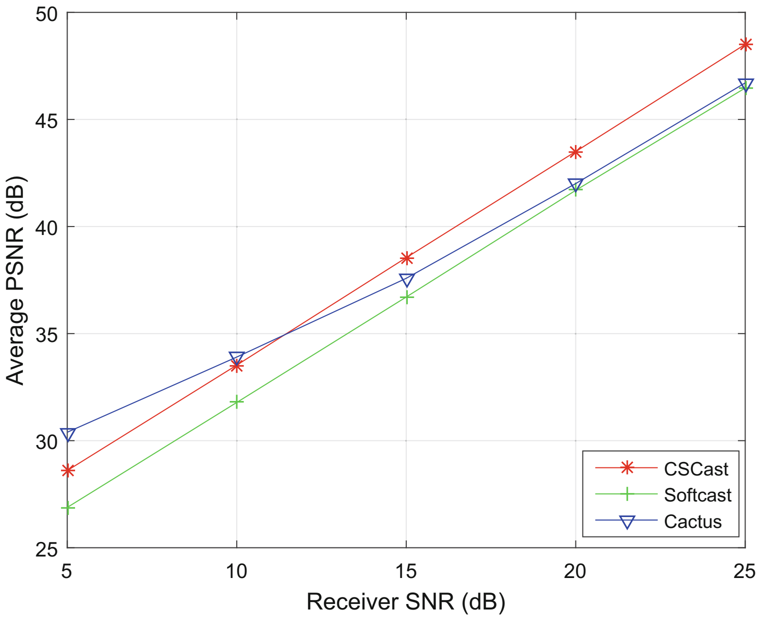

Fig. 5. Average PSNR comparison among different schemes.

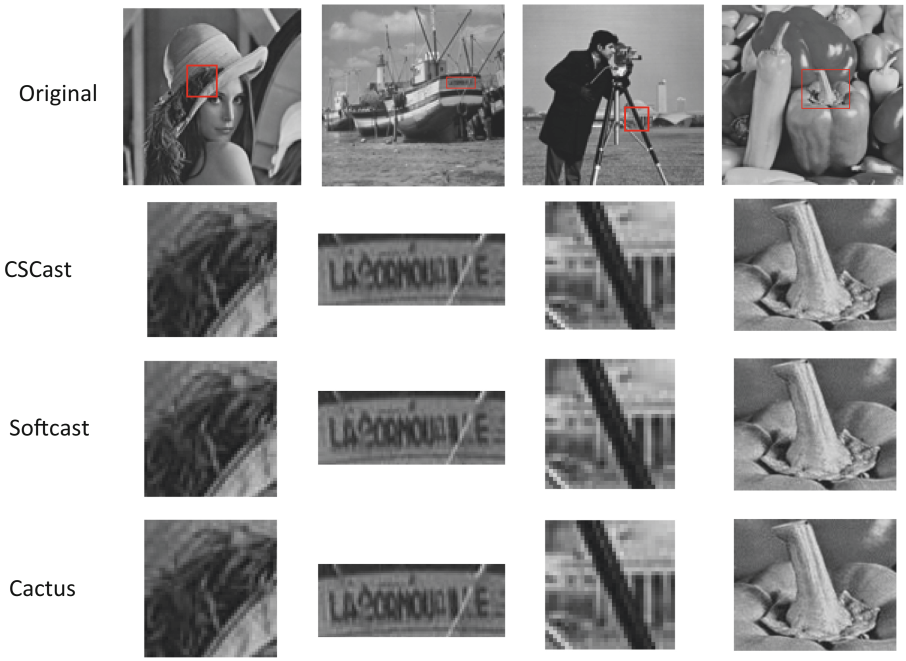

Fig. 6. Visual quality comparison.

increasing of SNR, the gain of CSCast over Softcast is increase, while the gain of Cactus over Softcast is decrease. When SNR >12 dB, the performance of CSCast better then Cactus. Specially, when SNR = 25 dB, CSCast achieves a maximum gain 1.8 dB over Cactus, and achieves a maximum gain 2.03 dB over Softcast, respectively.

The visual results with a 25 dB AWGN channel are shown in Fig. 6. It is easy to see that our proposed scheme achieves better visual quality than the reference schemes.

(3) Overhead Comparison

In Softcast and Cactus, it needs to transmit the power scaling factors with reliable digital method as in our scheme. Since the DCT block size is 8×8 in the two schemes, there are 64 metadata per image. In CSCast, we use CDF97 with level $L = 5$ to de-correlate. Therefore, there are only 16 metadata sent to receiver by using digital method. In addition, receiver needs generate the measurement matrix Φ from a pseudo random number, which negotiated with transmitter. Therefore, CSCast only needs 17 metadata, while others schemes need 64 meatdata. Comparing to SoftCast and Cactus, CSCast can save about 75% overhead.

4 Conclusion

We present an analog images communications system called CSCast which adopts CDF 9/7 to perform decorrelation transform and BCS to resist channel noise. We give out the appropriate value of power scaling factor α. According to our analysis, CSCast can save about 75% overhead by comparing with schemes based on Softcast. Simulation shows that the performance of CSCast outperforms over Softcast in all SNR range, and better than Cactus in high SNR range.

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