Perceptually Weighted Compressed Sensing for Video Acquisition

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Abstract: Efficient video acquisition and coding techniques have received increasing attention due to the wide spread of multimedia telecommunication. Compressed Sensing (CS) is an emerging technology, which enables acquiring video in a compressed manner. CS proves to be very powerful for energy constrained devices that benefit from processing at lower sampling rates. In this paper, a framework for compressed video sensing (CVS) that relies on an efficient fixed perceptual weighting strategy is adopted for acquisition and recovery. The proposed compressed sensing strategy focuses the measurements on the most perceptually pronounced coefficients. Three weighting schemes are developed and compared with standard CS. Simulation results demonstrate that the proposed framework provides a significant improvement in its three different setups over standard CS in terms of both standard and perceptual objective quality assessment metrics.

1 INTRODUCTION

Source coding techniques aim to reduce statistical redundancies inherited in the signal under concern. Traditional coding methods achieve this task by first acquiring the full signal at Nyquist rate, then transforming it to a suitable sparse domain, where the highest values coefficients are to be entropy coded and transmitted. In recent video coding standards, perceptual properties of the human have played an increasing role as an intrinsic measure of redundancy. The aim of perceptual coding is to transmit only the most important perceptual coefficients. One aspect of Human Visual System (HVS) that is exploited in recent coding standards such as H.264/MPEG-4 AVC (ITU-T 2003), and H.265/HEVC (Sullivan *et al.* 2013) is that the sensitivity of human eyes to low frequency components is larger than high frequency ones. A survey and recent developments on perceptual video coding techniques can be found in literature (e.g., Lee and Ebrahimi 2012, Lin and Zhang 2013).

Despite the efficiency of the legacy video coding systems, they still suffer from the unresolved obligation to sample the signal at the Nyquist rate. This means that high storage capacity is required. However, only small part of coefficients will be transmitted. This rather high sampling rate represents an obstacle for resource constrained acquisition devices.

Compressed Sensing (CS), first proposed by Donoho (2006), is an emerging theory that comes with a non-conventional solution to this problem. CS theory promotes accurate signal recovery using a much lower sampling rate compared to the Nyquist rate. This is guaranteed for signals that have sparse or compressible representation in some domain. CS has found a remarkable potential in many diverse fields (Qaisar *et al.* 2013), especially for multimedia acquisition and sampling. CS enables sensing directly in a compressed manner. Hence, it proves to be very beneficial for resource limited devices as mobile cameras or sensor nodes in wireless sensors networks (WSN).

Weighted l_1- minimization techniques are proposed in literature (e.g., Candes *et al.* 2008, Friedlander *et al.* 2011), to improve CS signal recovery by assigning different weights to different signal components according to their importance. Mansour and Yilmaz (2012) proposed adaptive CS system for video acquisition in which previously reconstructed frames are utilized to draw an estimation about the support of subsequent frames. This estimated support is fed back from the decoder to the encoder to focus the measurements of subsequent frame on the most probable non-zero coefficients. Then, weighted l_1- minimization

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recovery is used at the decoder to focus the recovery on this estimated support components.

Perceptual-based CS system for images, utilizing block-based 2D-DCT sparsity basis, has been introduced recently (Yang *et al.* 2009). In that work, the image is first transformed to the transform domain. Then, JPEG quantization tables are utilized to derive the weighting coefficient for the encoding process. Other perceptual based CS work that utilize wavelet transform as sparsity basis has been also presented (Lee *et al.* 2013). In that work, authors utilize wavelet layered structure by applying different measurement matrices and different weights for each wavelet block.

In this paper, we employ perceptual features inspired by recent video coding systems into the CS framework aiming to low complexity video acquisition and encoding system with improved perceived quality. To this end, simple perceptual based weighting strategy is adopted and embedded in the sensing matrix and/or recovery algorithm. Embedding the proposed weighting strategy in the sensing matrix enables the proposed system to directly acquire the most important perceptual information from the video signal. Our strategy mainly differs from previous adaptive and perceptual CS work in that, our perceptual weights are fixed. Consequently, the proposed system does not involve weighting updates or feedback. We propose three perceptual setups: applying perceptual weighting at decoder side, at encoder side, and at both encoder and decoder sides.

The rest of the paper is organized as follows: Section 2 presents a brief theoretical background for CS theory, and its application for video signals. The proposed system is presented in Section 3. Section 4 is dedicated for presenting our simulation results. Conclusion and future work are drawn in Section 5.

2 BACKGROUND

2.1 Compressed Sensing

Traditional coding techniques are based on an overwhelmingly high sampling acquisition of the full signal. CS theory guarantees accurate and robust recovery for signals having sparse or compressible representation in some basis with much lower sampling rate than Nyquist rate.

Suppose the signal $\mathbf{x} \in \mathbb{R}^N$ is to be acquired, CS involves obtaining a vector $\mathbf{y} \in \mathbb{R}^M$, $M \ll N$ such that:

$$\mathbf{y} = \mathbf{\Phi}\,\mathbf{x} \tag{1}$$

Where $\mathbf{\Phi} \in \mathbb{R}^{M\mathrm{x}N}$ is the sensing matrix. For accurate recovery, the sensing matrix should satisfy some properties such as Restricted Isometry Property (RIP) and incoherence (Donoho 2006). Random matrices are proved to satisfy RIP and universal incoherence with any fixed orthonormal basis.

The signal $\mathbf{x}$ should be sparse or compressible in some basis:

$$\mathbf{x} = \mathbf{\Psi}\boldsymbol{\alpha} \tag{2}$$

Where $\boldsymbol{\alpha} \in \mathbb{R}^N$ is the sparse transform coefficients of $\mathbf{x}$ in basis $\mathbf{\Psi}$. Consequently:

$$\mathbf{y} = \mathbf{\Phi}\mathbf{\Psi}\boldsymbol{\alpha} = \mathbf{A}\boldsymbol{\alpha} \tag{3}$$

Where $\mathbf{A} = \mathbf{\Phi}\mathbf{\Psi}$. It is required at the decoder side to recover $\mathbf{x}$ from $\mathbf{y}$, which is under-determined system of linear equations. Many results (e.g. Candes *et al.* 2006a, Donoho 2006) show that solving general l_1-minimization problem defined in (4) can stably and robustly recover *k*-sparse signals form only $M \geq c.k.\log\frac{N}{k}$ i.i.d Gaussian random measurements.

$$\boldsymbol{\alpha}^* = \underset{\boldsymbol{\alpha}\in\mathbb{R}^N}{\operatorname{argmin}} \|\boldsymbol{\alpha}\|_1 \ \mathrm{s.t.}\ \|\mathbf{y} - \mathbf{A}\boldsymbol{\alpha}\|_2 \leq \epsilon \tag{4}$$

Where $\boldsymbol{\alpha}^* \in \mathbb{R}^N$ is the optimal reconstructed sparse representation of the signal, and $\|.\|_p$ is the p^{th} order norm. If the signal has best *k*-term approximation defined by $\mathbf{x_k}$, the recovery error of (4) is governed by the following equation (Candes *et al.*, 2006b):

$$\|\mathbf{x}^* - \mathbf{x}\|_2 \leq \mathrm{C}_1.\epsilon + \mathrm{C}_2.\frac{\|\mathbf{x} - \mathbf{x}_\mathrm{k}\|_1}{\sqrt{\mathrm{k}}} \tag{5}$$

For well- behaved constants C_1 and C_2.

This means that, for compressible signals, the recovery error is proportional to l_1 −norm of unconsidered coefficients. Moreover, collecting measurements $\tilde{\mathbf{y}} = \mathbf{\Phi}\mathbf{x}_k$, can improve the recovery error (Mansour and Yilmaz 2012) .

With availability of prior information about signal support, weighted l_1-minimization has been proved to be an efficient way for enhancing signal recovery (Friedlander *et al.* 2011). Let $\widetilde{\mathrm{T}} \subset \{1,2,\ldots.N\}$ represent support estimation, and $\widetilde{\mathrm{T}}^{\mathrm{c}}$ is its complement. The recovery problem can be defined as:

$$\boldsymbol{\alpha}^* = \underset{\boldsymbol{\alpha}\in\mathbb{R}^N}{\operatorname{argmin}} \|\boldsymbol{\alpha}\|_{\mathrm{w},1} \ \mathrm{s.t.}\ \|\mathbf{y} - \mathbf{A}\boldsymbol{\alpha}\|_2 \leq \epsilon \tag{6}$$

Where $\|\boldsymbol{\alpha}\|_{\mathrm{w},1} = \sum_{i=1}^{N} \mathbf{w_i}|\boldsymbol{\alpha}_\mathbf{i}|$ and the weight coefficients vector is defined by:

$$\mathbf{w_i} = \begin{cases} \omega\,, \mathrm{i} \in \widetilde{\mathrm{T}} \\ 1\,, \mathrm{i}\ \in \widetilde{\mathrm{T}}^{\mathrm{c}} \end{cases} \tag{7}$$

Where $0 \leq \omega \leq 1$. By applying smaller weights for the estimated support coefficients, the recovery algorithm forces the solution to focus on these coefficients (Candes *et al.* 2008). Define support accuracy $\gamma = \frac{|\widetilde{T}\cap T_0|}{|\widetilde{T}|}$, which is the accuracy of the estimated $\widetilde{T}$ with respect to original support T_0. The reconstruction error in this case can be given as (Friedlander *et al.* 2011) :

$$\|\mathbf{x}^* - \mathbf{x}\|_2 \le C_0(\gamma) + C_1(\gamma)k^{-\frac{1}{2}}(\omega \left\|\mathbf{x}_{\widetilde{T}\cap T_0^c}\right\|_1 + \left\|\mathbf{x}_{\widetilde{T}^c\cap T_0^c}\right\|_1) \quad (8)$$

Equation (8) indicates that the recovery error depends on the weights and support accuracy. Using an accurate estimate of $\widetilde{T}$ and well-adjusted weights, the estimation error can decrease. In this paper, we propose using a support estimate based on the human eye sensitivity to different coefficients. The proposed compressed sensing strategy aims to focus the error in the less perceived coefficients.

2.2 Compressed Video Sensing

Video signals, despite having a huge quantity of data pixels, are characterized with high correlation between different pixels both in spatial and temporal directions. Theoretically speaking, video signals have nearly sparse (compressible) representation in some domain. As such, CS is very suitable for acquisition, coding, and transmission of video signals. Compressed video sensing (CVS) has been shown to be a practical alternative to traditional image and video coding techniques with respect to resources and measurements (Wahidah *et al.* 2011). Many sparsifying transforms are proposed in literature such as FFT, DCT, and Wavelet transforms (Sharma *et al.* 2012). DCT is commonly used in recent image and video standard coding techniques. It proves efficiency in representing most of the signal energy by small number of non-zero coefficients. For its efficacy, 2D-DCT/IDCT is utilized in our work as a sparsifying basis for individual frames.

3 PROPOSED SYSTEM

One of the main features of human eye perception is frequency discrimination. 2D-DCT/IDCT is exploited here as sparsity basis. DCT basis has structured sparsity and energy compaction properties. The most important coefficients for human perception, which are the low frequency coefficients, are located in predetermined locations at top left corner of 2D-DCT transform matrix. In addition to its perceptual importance, low frequency coefficients tend to have the largest values. Consequently, perceptual based support estimation goes beyond being a good guess of the location of the largest coefficients in the actual signal. Fig. 1 shows one frame of widely used Container video sequence (Arizona State University 2014) at the top and its 2D-DCT representation at the bottom. It can be seen that most of the energy concentrated in low frequency components at top left corner.

In the proposed algorithm, we follow the suit of Mansour and Yilmaz (2012) in using weighting coefficients for compressible signals. However, we choose the support estimate to conform to the eye perception properties. This choice proves to improve the perceived quality of video signal. Let $\widehat{T} \subset \{1,2,\dots.N\}$ represent the set of indices of the most visually important coefficients, we can term it as "visual support". Support accuracy plays an important role in enhancing the recovery performance (Friedlander *et al.* 2011). The higher the support accuracy, the higher the improvements achieved in the reconstructed signal.

For example, empirical results show that our support accuracy for $|\widehat{T}| = 0.2\,N$ is in range of 0.6 and 0.7. This means that the visual support estimate in this case intersects with the actual support of the signal with a percentage 60%-70% over all the frames.

Three different setups can be used to embed visual weighting in the compressed sensing and recovery process. The first setup embeds perceptual weighting at the decoder side only, the second setup utilize perceptual weighting at the encoder side only, while the third setup applying perceptual weighting at both the encoder and decoder sides. Fig. 2 shows the framework for the proposed three setups. To fully exploit the support accuracy, the weights and support sizes for the three setups are adjusted statistically from a set of model tests. Their optimal values are as shown in Table 1. The details for measurements and recovery for the three setups are explained below.

3.1 Setup 1: Standard CS with Perceptual Weighted Recovery

In this setup, standard measurements are obtained at the encoder side while perceptually weighted recovery is used at the decoder side. The measurements are acquired as in (1). Then the signal can be recovered by solving weighted l_1-minimization problem (6). The weighting strategy can be defined as in (7) replacing $\widetilde{T}$ with visual support estimate $\widehat{T}$.

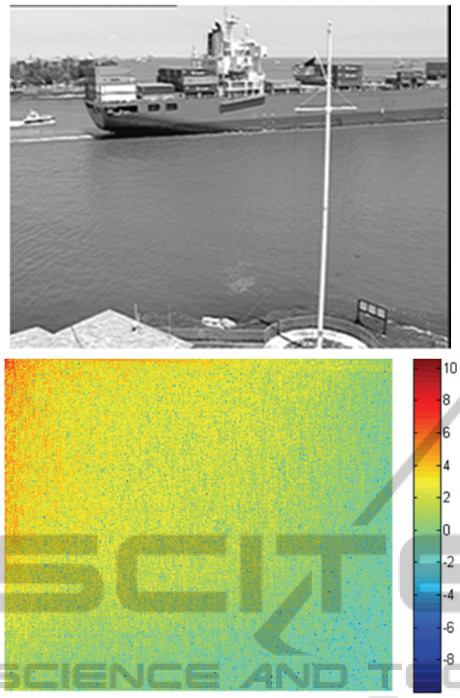


Figure 1: One video frame from Container sequence and its 2D-DCT transform coefficients.

3.2 Setup 2: Perceptual CS with Standard Recovery

In this setup, the perceptual weighting is adopted at the encoder side. While at the decoder side, standard l_1-minimization recovery is employed. The following weighting strategy is adopted:

$$\mathbf{w_i} = \begin{cases} 1 \text{ , i} \in \widehat{\mathrm{T}} \\ \omega \text{ , i } \in \widehat{\mathrm{T}}^{\mathrm{c}} \end{cases} \tag{9}$$

According to (9), the coefficients related to the visual support will be acquired fully. On the other hand, the effect of the coefficients outside the visual support is downplayed by factor ω. Define weight coefficients matrix $\mathbf{W}$ and perceptual weighting matrix $\mathbf{S}$ as follows:

$$\mathbf{W} = \mathrm{diag}(\mathbf{w_i}) \tag{10}$$

$$\mathbf{S} = \mathbf{\Psi W \Psi^T} \tag{11}$$

Hence the observation vector is represented as:

$$\tilde{\mathbf{y}} = \widetilde{\mathbf{\Phi}}\mathbf{x} = \mathbf{\Phi S x} = \mathbf{\Phi \Psi} \widetilde{\boldsymbol{\alpha}} \tag{12}$$

Where $\widetilde{\mathbf{\Phi}} = \mathbf{\Phi S}$ is the new sensing matrix, and $\widetilde{\boldsymbol{\alpha}} = \mathbf{W}\boldsymbol{\alpha}$ is visually weighted transform coefficients. Then, the reconstructed signal can be obtained by solving the following standard l_1- minimization problem:

$$\boldsymbol{\alpha}^* = \underset{\widetilde{\boldsymbol{\alpha}} \in \mathbb{R}^{\mathrm{N}}}{\mathrm{argmin}} \; \|\widetilde{\boldsymbol{\alpha}}\|_1 \; \mathrm{s.t.} \; \|\tilde{\mathbf{y}} - \mathbf{A}\widetilde{\boldsymbol{\alpha}}\|_2 \leq \epsilon \tag{13}$$

3.3 Setup 3: Perceptual CS with Perceptual Weighted Recovery

In this setup, the observation vector is defined as in (12): $\tilde{\mathbf{y}} = \widetilde{\mathbf{\Phi}}\mathbf{x}$. Then the recovery is done by solving the following weighted l_1- minimization problem:

$$\boldsymbol{\alpha}^* = \underset{\widetilde{\boldsymbol{\alpha}} \in \mathbb{R}^{\mathrm{N}}}{\mathrm{argmin}} \; \|\widetilde{\boldsymbol{\alpha}}\|_{\mathrm{w},1} \; \mathrm{s.t.} \; \|\tilde{\mathbf{y}} - \mathbf{A}\widetilde{\boldsymbol{\alpha}}\|_2 \leq \epsilon \tag{14}$$

In this setup, the weighting strategy at the decoder side is similar to Setup 1 which is defined by (7) replacing $\widetilde{\mathrm{T}}$ with visual support estimate $\widehat{\mathrm{T}}$. While at the encoder side, the weighting strategy is similar to Setup 2 as defined by (9).

Table 1: List of different setups and optimal visual support size and weights.

Sampling Scheme	Optimal visual support size	Optimal weight
Standard Setup	-	-
Setup 1	$0.085\, N\, e^{3.23\frac{M}{N}}$	0.3
Setup 2	$0.058\, N\, e^{3.09\frac{M}{N}}$	0.1
Setup 3	$0.85\, M$	0

4 SIMULATION RESULTS

The proposed perceptual compressed sensing setups are applied to different test video sequences (Y component of 4:2:0 sampling, 100 frames each). In the following we present sample results. The video sequences considered here are Container and News (Arizona State University 2014), they are both CIF resolution (352x288) with a frame rate of 30fps. Random measurements are used for each individual frame. Due to large scale nature for images, block diagonal sensing matrix in which the diagonal is populated with random sub-matrices is utilized (Park *et al.* 2011). The dimension of each diagonal sub-matrix is M_bxN_b, where N_b is block length, and M_b is the number of measurements taken from each block. Block length is selected in our system as $N_b = 256$. 2D-DCT for the full frame is utilized as sparsifying transform. The recovery algorithm utilized here is gradient projection for sparse reconstruction (GPSR) (Figueiredo *et al.* 2007, 2009) with parameters settings as: (initialization is done as $\mathbf{\Phi}^T\mathbf{y}$, debias phase is on, continuation is on, and stopping criteria

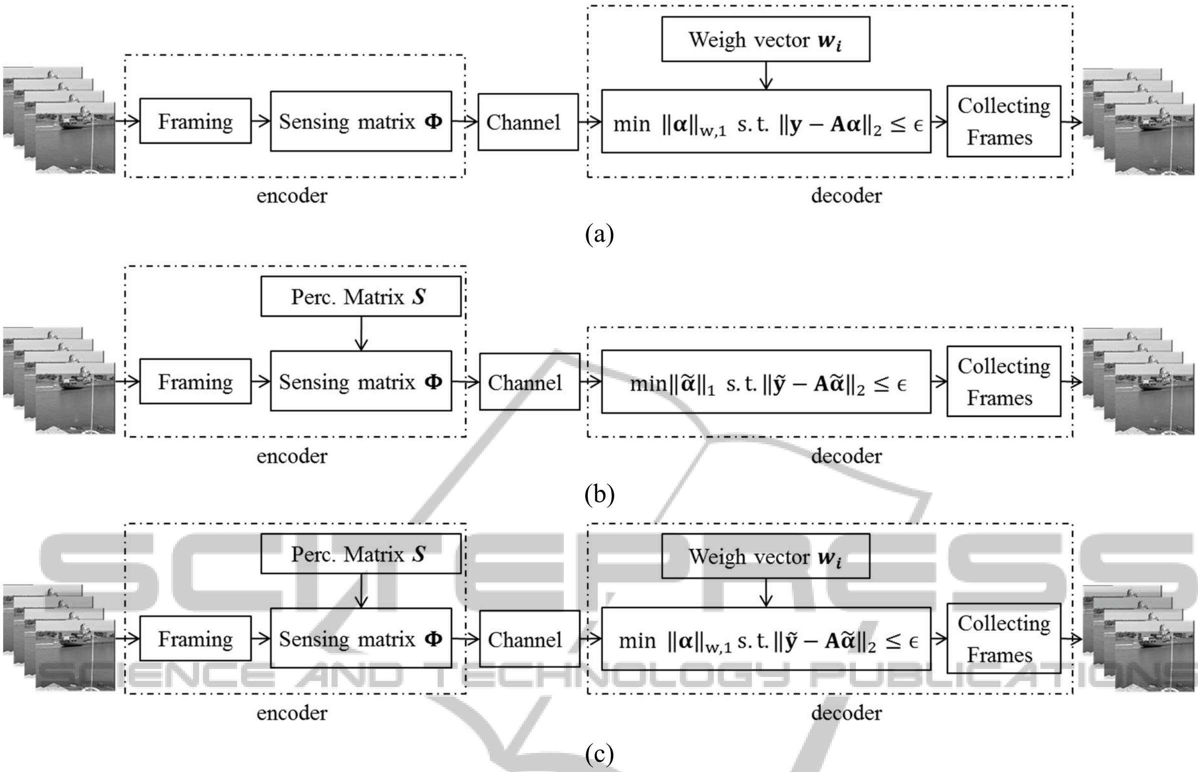


Figure 2: Framework for different setups (a) standard CS with perceptual recovery, (b) Perceptual CS with standard recovery, and (c) perceptual CS with perceptual recovery.

is when the relative change of objective function reaches ToleranceA=0.001 for the first phase and ToleranceD = $5\text{x}10^{-5}$ for debias phase). All simulations are performed by MatlabR2013a (MathWorks 2013). Two different quality assessment metrics are used for performance evaluation, namely, signal to noise ratio SNR and structural similarity SSIM index. SNR is in dB and is defined by (Friedlander *et al.* 2011):

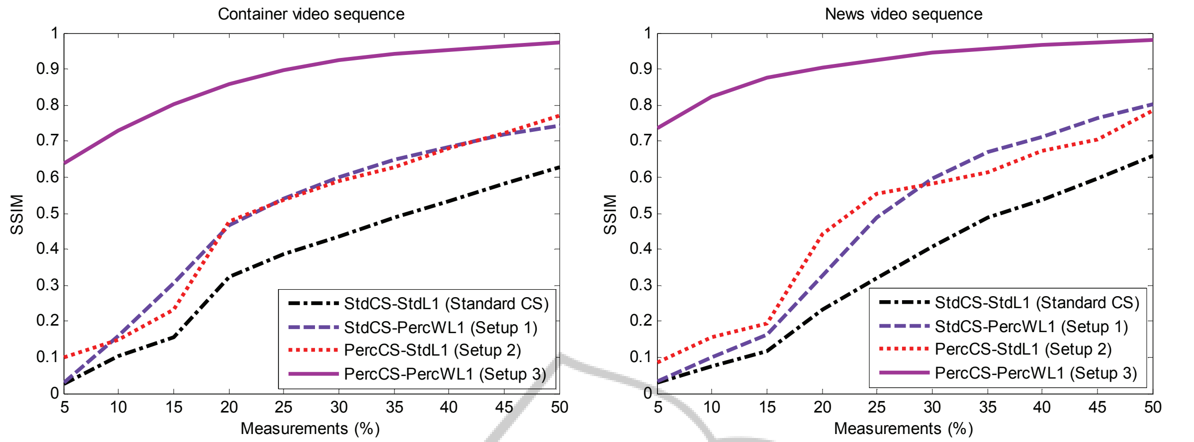
$$\mathrm{SNR}(\mathbf{x}, \mathbf{x}^*) = 10 \ \log_{10} \frac{\|\mathbf{x}\|_2^2}{\|\mathbf{x} - \mathbf{x}^*\|_2^2} \qquad (15)$$

Where $\mathbf{x}$ is the original and $\mathbf{x}^*$ is the recovered signal. $\|\mathbf{x}\|_2^2$ represents the energy of the original signal and $\|\mathbf{x} - \mathbf{x}^*\|_2^2$ represents the mean square error of the recovered signal.

On the other hand, SSIM estimates the perceived errors. It is consistent with human eye perception. SSIM considers the perceived change in structural information in the image (Wang *et al.* 2004a, 2004b). Fig. 3 and Fig. 4 show rate distortion (RD) curves in terms of SSIM and SNR, respectively, for the proposed three setups versus the standard CS for Container and News video sequences. RD curves show the performance of different systems with different measurement rates (MRs).

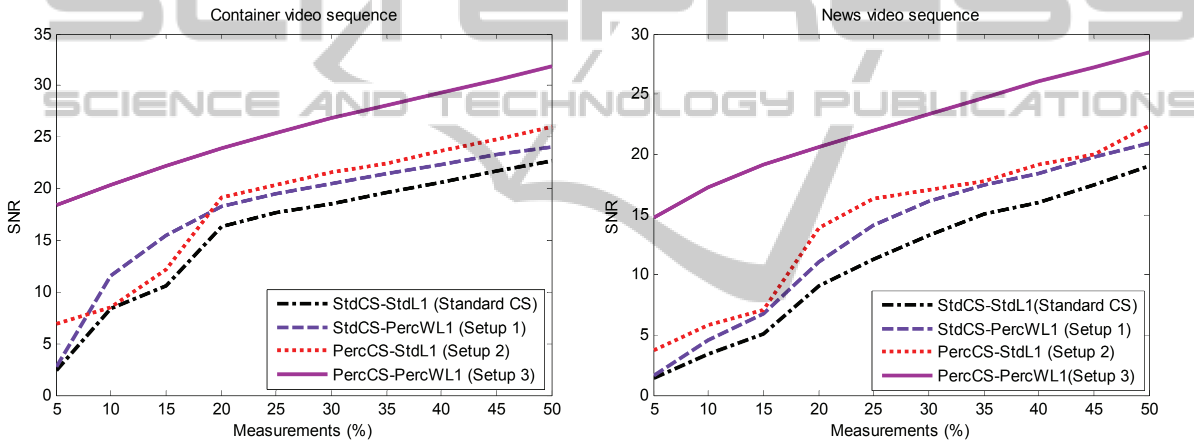
The results show that applying perceptual weighting at either the decoder side or the encoder side (Setups 1 and 2 respectively) improves the performance over the standard CS scheme especially for higher measurement rates. Moreover, applying perceptual weighting at both the encoder and decoder sides (Setup 3) has shown the best performance among all setups with its most pronounced improvement at lower measurement rates. Fig.3 shows that, at MR=5% for example, while Setup 1 achieves no SSIM gain over the standard CS for both video sequences, Setup 2 achieves an SSIM gain of ~ 0.07 (7% of the full scale (FS)) for Container, and ~ 0.05 (5% of FS) for News. Moreover, Setup 3 achieves an SSIM gain of ~ 0.61 (61% of FS) for Container and ~ 0.7 (70% of FS) for News. Taking another point at MR=25%, for example. For Container, both Setup 1 and 2 achieve an SSIM gain of ~ 0.15 (15% of FS) and for News, Setup 1 and Setup 2 achieve an SSIM gain of ~ 0.17 (17% of FS) and ~ 0.24 (24% of FS), respectively. Moreover, at this sampling rate (MR=25%), Setup 3 achieves an SSIM gain of ~ 0.51 (51% of FS) for Container and ~ 0.61 (61% of FS) for News.

These results can be viewed from another angle. Thinking of a system requiring a specified SSIM, the



(a) (b)

Figure 3: SSIM rate distortion curves for (a) Container sequence, and (b) News sequence, for different CS setups versus standard CS scheme.



(a) (b)

Figure 4: SNR rate distortion curves for (a) Container sequence, and (b) News sequence, for different CS setups versus standard CS scheme.

proposed setups are capable of achieving this SSIM values with much lower measurement rates compared to the standard CS scheme. For example, we can see from Fig. 3 (a) that, for Container sequence, an SSIM of 0.64 can be obtained using only 5% measurement rate with Setup 3 and 32% for Setups 1 and 2, while it requires more than 50% measurement rate for standard CS to achieve the same SSIM value. Hence, our proposed systems achieve better perceived video quality using lower complexity acquisition devices.

In addition, proposed schemes also provide significant improvements over the standard scheme in terms of the SNR metric. Fig. 4 shows that, at MR=5% for example, while Setup 1 achieves no SNR improvement over standard CS for both video sequences, Setup 2 achieves ~ 4.18 dB gain in case of Container sequence and ~ 2.06 dB gain for News sequence. Moreover, Setup 3 achieves ~ 15.62 dB gain for Container sequence, and ~ 13.12 dB gain for News sequence. For another point at MR=25% for example, Setup 1 achieves gain of ~ 1.82 dB and ~ 2.9 dB for Container and News sequences, respectively. Setup 2 achieves gain of ~ 2.77 dB and ~ 5.06 dB for Container and News sequences, respectively. Moreover, Setup 3 achieves gain of ~ 7.77 dB and ~10.7 dB for Container and News sequences, respectively.

In other terms, considering a system that require certain SNR, our proposed setups are capable of achieving this SNR values with much lower measurement rates compared to the standard CS scheme. For example, we can see from Fig. 4 (a) for Container sequence that, an SNR of 18 dB can be obtained using only MR=5% for Setup 3 and MR=

20% for Setups 1 and 2, while it requires 30% for the standard CS scheme to achieve the same SNR value. Consequently, our proposed systems can achieve better video quality using lower complexity acquisition devices.

5 CONCLUSION AND FUTURE WORK

In this paper, an efficient perceptual weighting strategy is adopted into CS framework for video acquisition to improve the perceived quality of the reconstructed signal. This goal has been achieved through three different setups. The performance evaluation for different setups demonstrates remarkable improvements over standard CS in terms of both SNR and SSIM metrics. While Setup 1 and 2 are competing, Setup3 shows the best performance among all setups. Setup 3 can achieve a peak SSIM gain of ~ 61% on FS for Container sequence and ~ 70% on FS for News sequence. In addition, Setup 3 can achieve a peak SNR gain of ~ 15.62 dB for Container sequence, and ~ 10.7 dB for News sequence. The efficacy of our proposed systems for low complexity acquisition devices has been demonstrated.

This work is applied for single view video and exploits only sparsity in spatial direction for separate frames. As a future work, we aim to give attention to inter-frame correlation to exploit the sparsity in the temporal direction of the video rather than exploiting only the sparsity in the spatial direction. This can improve the compression order obtained through compressed sensing. In addition, we aim to extend our perceptual based system to multi-view video coding. Quantization effects also can be considered for future work.

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