DISTRIBUTED COMPRESSION VIDEO SENSING

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ABSTRACT
Low-complexity video encoding has been applicable to several emerging applications. Recently, distributed video coding (DVC) has been proposed to reduce encoding complexity to the order of that for still image encoding. In addition, compressive sensing (CS) has been applicable to directly capture compressed image data efficiently. In this paper, by integrating the respective characteristics of DVC and CS, a distributed compressive video sensing (DCVS) framework is proposed to simultaneously capture and compress video data, where almost all computation burdens can be shifted to the decoder, resulting in a very low-complexity encoder. At the decoder, compressed video can be efficiently reconstructed using the modified GPSR (gradient projection for sparse reconstruction) algorithm. With the assistance of the proposed initialization and stopping criteria for GRSR, derived from statistical dependencies among successive video frames, our modified GPSR algorithm can terminate faster and reconstruct better video quality. The performance of our DCVS method is demonstrated via simulations to outperform three known CS reconstruction algorithms.

Index Terms—compressive video sensing, (distributed) compressive sampling/sensing, distributed video coding

1. INTRODUCTION
Low-complexity video coding has been potentially applicable for several emerging applications, such as video conferencing with mobile devices and wireless visual sensor networks (VWSN) [1]. Since the low-complexity restriction for a video device, efficient video compression is challenging. Recently, distributed video coding (DVC) [2] based on the principle of distributed source coding (DSC) has been proposed to reduce video encoding complexity to the order of that for still image encoding while preserving a certain coding efficiency. In DVC, the major encoding computation burden can be shifted to the decoder, which is usually allowed to possess powerful computational capability in several real applications (e.g., VWSN)

However, for still image encoding, it is required to capture huge amounts of raw image data first, followed by performing some transformation operator (e.g., discrete wavelet transform, i.e., DWT), which is also computation-intensive [3]. Recently, with the advent of a single-pixel camera [4], compressive sensing (CS) [3]-[8] has been applicable to directly capture compressed image data efficiently. The compressed image can be reconstructed using some CS reconstruction algorithms at the decoder. Similar to DVC, the computation burden can be shifted to the decoder.

However, for compressing huge amounts of video data, it may not be efficient enough to only reduce the encoding complexity or only to individually apply CS to each frame without considering similarities among successive frames. In this paper, by integrating the respective characteristics of DVC and CS, a distributed compressive video sensing (DCVS) framework is proposed to simultaneously capture and compress video data. Almost all computation burdens can be shifted to the decoder where our modified GPSR (a kind of CS reconstruction algorithm) incorporating with the statistical dependencies among successive frames is exploited to reconstruct video data.

The characteristics of our DCVS includes: (i) very low-complexity encoder: only general CS measurement process (described in Sec. 2.3) will be individually applied to each frame; and (ii) very efficient decoder: by applying the proposed initialization and stopping criteria for GRSR (described in Sec. 4), the convergence speed and reconstructed video quality using our modified GPSR can be, respectively, faster and better than those using the original GPSR [9], TwIST (two-step iterative shrinkage/thresholding) [10], and OMP (orthogonal matching pursuit) [11].

2. RELATED WORKS
In this section, several related works, including DSC, DVC, CS, compressive image/video sensing, and distributed CS will be reviewed first. Then, the proposed DCVS based on DVC and CS will be addressed in Sec. 3.

2.1. Distributed source coding (DSC)
Assume that and are two statistically dependent discrete signals, which are encoded independently but decoded jointly. Slepian-Wolf theorem [2] states the achievable rate region for lossless coding is defined by and , and are the rates for encoding and , respectively, , are the conditional entropies of and , respectively, and is the joint entropy of and . Then, Wyner-Ziv theorem [2] states DSC with side information (SI) for lossy coding. Assume that is known as the SI of . The conditional distortion function for is unchanged no matter is available only at the decoder, or both at the encoder and decoder.

2.2. Distributed video coding (DVC)
In DVC [1][2], based on Wyner-Ziv theorem, the statistical dependency between a frame and its SI is modeled as a virtual correlation channel, where can be viewed as a noisy version of . The correlation between and can be modeled as a Laplacian distribution as follows:

\[
P(W(a,b)-S(a,b)) = \frac{\alpha}{2} e^{-\alpha |W(a,b)-S(a,b)|},
\]

where and are the (a, b)-th pixel in and S, respectively, and is the standard deviation of (Wyner-Ziv bits) derived from the channel-encoded version of W according to the request from the decoder via the feedback channel. The decoder uses the received Wyner-Ziv bits and the SI derived from previous decoded frames to perform channel decoding to correct some “errors” in for the reconstruction of . In transform-domain DVC, the Wyner-Ziv bits are generated by performing some transformation operator, followed by performing
scalar quantization and channel encoding. Hence, the complexity of the DVC encoder is similar to that of still image encoder consisting of transformation, quantization, and entropy encoding.

2.3. Compressive sensing (CS)
Assume that a sparse basis matrix $\Psi$ with size $N \times N$ can provide a $K$ sparse representation for a real value signal $x$ with length $N$. That is, $x$ can be represented as $x = \Psi \theta$ with length $N$ can be well approximated using only $K << N$ non-zero entries. CS [3]-[8] states that $\theta$ can be accurately reconstructed by taking only:

$$ M = O(K \log(N/K)) $$

where $K < M << N$, linear and non-adaptive measurements from:

$$ y = \Phi x = \Phi \Psi \theta = A \theta, $$

where $\Phi$ is an $M \times N$ measurement matrix that is incoherent with $\Psi$, and $A = \Phi \Psi$. More specifically, the $M$ measurements in $y$ are random linear combinations of the entries of $\theta$, which can be viewed as the compressed and encrypted version of $x$. Currently, it is unclear that how to efficiently quantize and entropy-encoded the $M$ measurements [5], which will be left for the future research. To reconstruct $\theta$ from $y$, CS is based on solving the convex optimization problem [3]-[10] (e.g., linear programming or GPSR [9]) or some iterative greedy algorithms (e.g., OMP [11]). Finally, $x$ can be reconstructed via $\hat{x} = \Psi \hat{\theta}$, where $\hat{\theta}$ is the reconstructed $\theta$.

2.4. Compressive image/video sensing
In compressive image sensing, if an image $x$ can be sparsely represented using a basis $\Psi$ (e.g., DWT), $x$ can be compressed via the CS technique in Eq. (3) and reconstructed via some CS recovery algorithms [3]-[11]. On the other hand, compressive video sensing has been first proposed in [8], where each video block, at the encoder, is classified to be either sparse or non-sparse via a CS test. Each sparse block is compressed via CS, whereas each non-sparse block is fully sampled.

2.5. Distributed compressive sensing (DCS)
Distributed compressive sensing (DCS) [6] exploits both intrasignal and inter-signal correlation structures. Consider a sensor network scenario, several sensors measure signals that are each individually sparse in a certain basis and also correlated among sensors. In DCS, each signal is independently measured via a CS technique and jointly reconstructed at a collection point collecting measurements from multiple sensors.

3. DISTRIBUTED COMPRESSIVE VIDEO SENSING (DCVS)
In this section, the joint sparsity model of our DCVS is first described in Sec. 3.1 to show the guideline for exploiting the statistical dependencies among successive frames. In our DCVS encoder described in Sec. 3.2, each frame is independently compressed via a CS measurement process. In our DCVS decoder, each frame is jointly reconstructed using our modified GPSR incorporating the proposed initialization derived from DVC side information generation and the proposed stopping criteria derived from statistical dependencies among successive frames, described in Secs. 3.3-3.6. Note that our DCVS, at its current status, is only designed for single-view videos, which can be extended to multiview video scenario, and can be applicable in a WVSN.

3.1. Joint sparsity model
To exploit the correlation among successive frames, similar to [6], the joint sparsity model in our DCVS can be described as follows. Assume two successive frames, $x_t$ and $x_{t+1}$, in the same scene are visually similar, where $t$ is the time instant. That is, $x_t$ and $x_{t+1}$ should have similar common portion and respective unique portions. Conceptually, the two frames can be expressed as:

$$ x_t = x_c + x_{t, U}, $$

$$ x_{t+1} = x_c + x_{t+1, U}, $$

where $x_c$ is the similar/common portion between $x_t$ and $x_{t+1}$, $x_{t, U}$ and $x_{t+1, U}$ are the unique portions of $x_t$ and $x_{t+1}$, respectively. By treating $x_c$ as a reference frame for $x_{t+1}$, in conventional video coding, the encoder will perform motion estimation to find the predictor (similar to $x_c$) for $x_{t+1}$ and encode the difference (similar to $x_{t+1} - x_c$) between $x_{t+1}$ and its predictor. Hence, the compression of $x$ and $x_{t+1}$ can be achieved by approximating $x$ and $x_{t+1}$ respectively.

3.2. DCVS encoder
In DCVS, a video sequence consists of several GOPs (group of pictures), where a GOP consists of a key frame followed by some non-key frames. Conceptually, each key frame serves as a reference frame for its neighboring non-key frames. At our DCVS encoder shown in Fig. 1, without performing motion estimation, without needing any prior knowledge about correlation among successive frames, and without performing extra tasks (no additional burden) in the CS process described in Sec. 2.3, each frame $x_t$ (key frame or non-key frame) with size $N$ is compressed via the CS measurement process (Eq. (3)) as:

$$ y_t = \Phi x_t, $$

where $y_t$ is the measurement vector with size $M \times 1$ and $\Phi$ is the $M \times N$ measurement matrix described later. Based on the joint sparsity model in Sec. 3.1, the measurement rate ($MR$) of a key frame should be larger than that of a non-key frame. The $MR$ for a frame $x_t$ can be defined as $MR = M_t/N$.

3.3. Gradient projection for sparse reconstruction (GPSR)
At the decoder, each key frame $x_t = \Psi \theta_t$ with size $N$ is reconstructed via GPSR [9], which solves the convex unconstrained optimization problem as:

$$ x_t = x_c + x_{t, U}, $$

$$ x_{t+1} = x_c + x_{t+1, U}, $$

where $x_c$ is the similar/common portion between $x_t$ and $x_{t+1}$, $x_{t, U}$ and $x_{t+1, U}$ are the unique portions of $x_t$ and $x_{t+1}$, respectively.
\[
\min_{\theta} \frac{1}{2} \| y - A \theta \|_2^2 + r \| \theta \|_1,
\]  
(9)
where \( y \) is a \( M \times 1 \) vector, \( y = \Phi x \), \( A = \Phi \Phi \) is a \( M \times N \) matrix, \( \| \cdot \|_2 \) is the Euclidean norm (\( \ell_2 \) norm) of \( v \), \( \| \cdot \|_1 \) is the \( \ell_1 \) norm of \( v \), i.e., the sum of the absolute value of each component in \( v \), and \( r \) is a non-negative parameter. GPSR is essentially a gradient projection (GP) algorithm applied to a quadratic programming formulation of Eq. (9), in which the search path for each iteration is obtained by projecting the negative-gradient direction onto the feasible set [9].

Each key frame is reconstructed via GPSR [9] with default settings in the public GPSR code included in the “Fast CS using SRM” tool [7]. In GPSR, the default initial solution for \( \theta \) is a zero vector. The default stopping criterion of GPSR is that when the relative change in the number of nonzero components in \( \theta \) is smaller than a threshold \( T_\theta \) (default \( T_\theta = 0.01 \)), the algorithm will stop. Finally, the key frame \( x_t \) can be reconstructed via \( \tilde{\chi} = \Psi \tilde{\theta} \), where \( \tilde{\theta} \) is the final solution obtained by GPSR. Note that the used GPSR included in [7] is an older version. Recently, the latest version called GPSR 5.0 [9] providing a novel default stopping criterion has been released. However, our simulations show that the older version can provide a better tradeoff between reconstructed video quality and reconstruction complexity.

3.4. Side information (SI) generation
In DCVS, each non-key frame is reconstructed via GPSR with the proposed initialization and stopping criteria, derived from the statistical dependencies among successive frames. Before reconstructing a non-key frame \( x_t \), the decoder will generate its SI \( S_t \), first, which can be viewed as a noisy version of \( x_t \). Similar to DVC [2], SI can be generated by motion-compensated interpolation from previous reconstructed neighboring key frames. In DCVS, a very efficient frame rate up-conversion tool [12] is exploited to generate the SI for each non-key frame.

3.5. Initialization at DCVS decoder
In our modified GPSR for reconstructing each non-key frame \( x_t = \Psi \theta_t \), the initial solution for \( \theta_t \) is set to be by its SI \( S_t \) as follows: \( \tilde{\theta}_t^{(0)} = \theta_t \), i.e., \( \tilde{x}_t^{(0)} = S_t \), where \( \tilde{x}_t^{(0)} \) is the initial solution (at the 0-th iteration) for \( \theta_t \), \( S_t = \Psi \theta_t \), and \( \tilde{x}_t \) is the SI of \( x_t \). In the same scene, successive frames should have a certain similarity. Hence, the SI derived from the neighboring key frames for a non-key frame should be similar to this frame, even though the SI may be coarse due to fast motions, poor SI generation, or poor neighboring reconstructed key frames. Based on Sec. 3.1, the measurement rate for a non-key frame is usually set to be smaller than that of a key frame. To get a good reconstructed non-key frame, it is required to have a good initialization, followed by GPSR optimization where proper stopping criteria are required to get optimal or near-optimal solution after a small number of iterations.

3.6. Stopping criteria at DCVS decoder
It is usually difficult to decide when GPSR can stop without incurring excessive computation [9] and with sufficient reconstruction quality. At DCVS decoder, the stopping criteria for GPSR are designed based on the statistical correlation between the current non-key frame and its SI. Consider a non-key frame \( x_t \), its SI \( S_t \), and the reconstructed \( x_t \) at the i-th iteration, denoted by \( \tilde{x}_t^{(i)} \).

Based on Sec. 2.2, the correlation between \( x_t \) and \( S_t \) can be modeled as a Laplacian distribution with the parameter \( a(x_t, S_t) \). The more similar \( x_t \) and \( S_t \) are, the larger \( a(x_t, S_t) \) is. Similarly, \( \tilde{x}_t^{(i)} \) and \( S_t \) can be modeled by \( a(\tilde{x}_t^{(i)}, S_t) \) while \( \tilde{x}_t^{(i)} \) and \( x_t \) can be modeled by \( a(\tilde{x}_t^{(i)}, x_t) \). Obviously, if \( x_t \) can be perfectly reconstructed by \( \tilde{x}_t^{(i)}, a(\tilde{x}_t^{(i)}, x_t) = \infty \). Hence, if \( \tilde{x}_t^{(i)} \) can be found to maximize \( a(\tilde{x}_t^{(i)}, x_t) \), \( \tilde{x}_t^{(i)} \) should be very similar to \( x_t \). Initially, \( \tilde{x}_t^{(0)} = S_t \) and hence \( a(\tilde{x}_t^{(0)}, S_t) = \infty \). When \( i \) increases, \( a(\tilde{x}_t^{(i)}, S_t) \) will first decrease rapidly and then slowly decrease while \( a(\tilde{x}_t^{(i)}, x_t) \) will slowly increase. If excess iterations \( i \) becomes larger \( \) are performed, \( a(\tilde{x}_t^{(i)}, x_t) \) may decrease, i.e., \( \tilde{x}_t^{(i)} \) may begin to be distant from \( x_t \). However, at the decoder, \( x_t \) is unknown and only \( a(\tilde{x}_t^{(i)}, S_t) \) can be known. Under this circumstance, it is not guaranteed that when \( a(\tilde{x}_t^{(i)}, S_t) \) decreases and \( a(\tilde{x}_t^{(i)}, x_t) \) increases. Hence, the first stopping criterion can be determined as follows. When the relative change in the Laplacian parameter \( a(\tilde{x}_t^{(i)}, S_t) \) is smaller than a threshold \( T_a \), i.e.,

\[
|a(\tilde{x}_t^{(i)}, S_t) - a(\tilde{x}_t^{(i-1)}, S_t)| / a(\tilde{x}_t^{(i-1)}, S_t) \leq T_a,
\]  
(10)
the algorithm will stop.

On the other hand, the major goal of GPSR is to find the optimal \( \tilde{x}_t^{(i)} \) by minimizing Eq. (9), where \( \tilde{x}_t^{(i)} = \Psi \tilde{\theta}_t^{(i)} \). Without considering video characteristics, the solution obtained by minimizing Eq. (9) may be over-sparse, leading to lower visual quality. To preserve the video characteristic for a non-key frame, its SI, i.e., the correlations among this frame and its neighboring frames, can be exploited. By adding an extra term, a quality-preserving fitness function can be defined as:

\[
F(\tilde{x}_t) = W_1 F(\tilde{x}_t^{(i)}) + W_2 F(\tilde{x}_t^{(i-1)}),
\]
(11)
where \( F(\tilde{x}_t^{(i)}) \) is defined by Eq. (9) and \( F(\tilde{x}_t^{(i)}) \) is defined as:

\[
F(\tilde{x}_t^{(i)}) = \| \tilde{x}_t^{(i)} - \theta_0 \|_2,
\]
(12)
where \( S_t = \Psi \theta_0, \tilde{x}_t \) is the SI of \( x_t = \Psi \theta_0, \) and \( W_1 \) and \( W_2 \) are weighting coefficients, empirically set by 0.9 and 0.1, respectively. Initially, \( \tilde{x}_t^{(0)} = \theta_0, F(\tilde{x}_t^{(0)}) = 0, \) and \( i = 0. \) When \( i \) increases, \( F(\tilde{x}_t^{(i)}) \) will increase while \( F(\tilde{x}_t^{(i-1)}), \) i.e., Eq. (9), will decrease. The major goal to evaluate Eq. (11) is that while GPSR attempts to minimize \( F(\tilde{x}_t^{(i)}) \), the similarity between \( \tilde{x}_t^{(i)} \) and \( \theta_0 \) should be preserved to a certain degree. Hence, the second stopping criterion can be determined as follows. If \( F(\tilde{x}_t^{(i)}) \) in Eq. (11), when compared with the one obtained in the previous iteration, is increased, i.e., if

\[
F(\tilde{x}_t^{(i)}) - F(\tilde{x}_t^{(i-1)}) > 0,
\]
(13)
the algorithm will stop. In addition, when the relative change in Eq. (11) is smaller than a threshold \( T_f \) (default \( T_f = 0.001 \), i.e.,

\[
|F(\tilde{x}_t^{(i)}) - F(\tilde{x}_t^{(i-1)})| / F(\tilde{x}_t^{(i-1)}) \leq T_r,
\]
(14)
the algorithm will stop. This is the third stopping criterion.

Based on our simulations, when the measurement rate \( MR \) for a non-key frame is low, the initial solution (initialized by its SI) is already very close to the optimal solution. The algorithm can usually stop in few iterations, and the first stopping criterion is very suitable. When \( MR \) is high, the other two criteria should be also exploited. The stopping criteria at DCVS decoder for a non-key frame \( \tilde{x}_t^{(i)} \) at the i-th iteration can be summarized as follows:

(a) \( MR \) is low \((MR \leq 20\%); \) if Eq. (10) with \( T_a = 0.9 \) is satisfied, the algorithm will stop.

(b) \( MR \) is high \((MR > 20\%); \) if Eq. (11) with \( T_a = 0.9 \) is satisfied, the algorithm will stop.

(c) \( MR \) is medium \((MR \approx 50\%); \) if Eq. (12) with \( T_a = 0.9 \) is satisfied, the algorithm will stop.

(d) \( MR \) is high \((MR > 50\%); \) if Eq. (13) with \( T_a = 0.9 \) is satisfied, the algorithm will stop.
(b) MR is middle ($20\% < MR \leq 70\%$): if Eq. (10) with $T_a = 0.05$ or Eq. (13) is satisfied, the algorithm will stop.
(c) MR is high ($MR > 70\%$): if Eq. (14) is satisfied, the algorithm will stop.

The above-mentioned thresholds, $T_a$ and $T_F$, are empirically decided, and fixed for all test video sequences. Finally, $x_c$ can be reconstructed via $\hat{x}_c = \Psi \hat{\theta}$, where $\hat{\theta}$ is the final solution obtained by GPSR. Our DCVS decoding procedure is summarized in Fig. 2.

4. SIMULATION RESULTS

In this paper, two CIF (frame size: $352 \times 288$) video sequences (300 Y frames for each), Coastguard and Foreman, with GOP size = 3, and different measurement rates (MRs) were employed to evaluate the proposed DVCS method. For example, the average $MR = 30\%$ means that the MRs for each key and non-key frames are 50% and 20%, respectively. The three known sparse signal reconstruction algorithms, GPSR [9], TwIST [10], and OMP [11], with default settings were used for comparisons with our DCVS. The three algorithms were applied to each frame individually. For OMP [11], the reconstruction complexity will be too expensive if it is directly applied to a whole frame. As suggested by [8], OMP can be individually applied to each $32 \times 32$ block with good trade-off between CS efficiency and reconstruction complexity. The four evaluated algorithms used the same measurement matrix, SBHE [7] and the same basis matrix, DWT. The four algorithms possess the same low-complexity encoder (the same CS measurement process).

The average PSNR performances at different average MRs for the two sequences are shown in Fig. 3(a) and (b), respectively. The average reconstruction complexities (in seconds) for obtaining Fig. 3(b) are shown in Fig. 4(a). The average PSNR performances at different reconstruction complexities at $MR = 30\%$ for the Foreman sequence are shown in Fig. 4(b). It can be observed from Figs. 3 and 4(a) that the PSNR performances of our DCVS can outperform or be comparable with the three known algorithms, especially at low MRs, with lower or comparable reconstruction complexities. At lower MRs, initializing by SI in our method can achieve good performances while at higher MRs, all the four algorithms can achieve similar performances. For the Coastguard sequence with slower motions, the SI is more accurate than that of the Foreman sequence, and better performance can be achieved. Based on Fig. 4(b), the PSNR performances of our DCVS can significantly outperform the three known algorithms at the same reconstruction complexities.

5. CONCLUSIONS

In this paper, a distributed compressive video sensing (DCVS) framework is proposed to simultaneously capture and compress videos at the low-complexity encoder and efficiently reconstruct videos at the decoder. For future researches, the key components, such as measurement matrix and reconstruction algorithm, in compressive video sensing should be designed based on video characteristics. The theoretical number of measurements for signal perfect reconstruction in Eq. (2) should also be further reduced with side information incorporated. In addition, efficient quantization and entropy coding techniques for CS measurements should be investigated to achieve complete video compression.

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