LETTER

Resample-Based Hybrid Multi-Hypothesis Scheme for Distributed Compressive Video Sensing

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SUMMARY Multi-hypothesis prediction technique, which exploits inter-frame correlation efficiently, is widely used in block-based distributed compressive video sensing. To solve the problem of inaccurate prediction in multi-hypothesis prediction technique at a low sampling rate and enhance the reconstruction quality of non-key frames, we present a resample-based hybrid multi-hypothesis scheme for block-based distributed compressive video sensing. The innovations in this paper include: (1) multi-hypothesis reconstruction based on measurements reorganization (MR-MH) which integrates side information into the original measurements; (2) hybrid multi-hypothesis (H-MH) reconstruction which mixes multiple multi-hypothesis reconstructions adaptively by resampling each reconstruction. Experimental results show that the proposed scheme outperforms the state-of-the-art technique at the same low sampling rate.

key words: *distributed compressive video sensing (DCVS), multi-hypothesis (MH) reconstruction, compressed sensing (CS), measurement reorganization*

1. Introduction

Recent years have witnessed a rapid growth in real-time video sensing using wireless video sensor network (WVSN); the complexity of video signal and the limitation of communication resources pose significant challenges for video communication. Distributed compressive video sensing (DCVS) rises in response to the proper time and conditions. Known as the state-of-the-art algorithm in block-based DCVS, the multi-hypothesis prediction has been attached increasing attention [1]–[6]. Based on Johnson-Lindenstrauss (JL) lemma [7], the core of multi-hypothesis prediction algorithm is to create a prediction that is as close as possible to the original signal by recasting optimization from the ambient signal domain into the measurement domain. Transferring back from the lower dimension to the higher dimension would not be a one to one map, thus several regularizations have been proposed. In [1], Fowler proposed a single Tikhonov regularization which achieves acceptable performance and speeds up the reconstruction. Combing with the Tikhonov regularization, Chen [4] presented an elastic net-based scheme for DCVS which assumes the coefficient vector to be sparse. Moreover, instead of considering the sparsity of the coefficient vector, Azghani [6] incorporated the MH technique with the sparsity constraint on the frames and the Tikhonov regularization, and presented an iterative algorithm using ADMM technique. Compared with the Tikhonov-based scheme [1], although these methods [4] and [6] achieve better reconstruction quality, they are at the cost of higher computational complexity. Furthermore, the prediction generated from this map can be likely inaccurate at a low sampling rate, which can lead to poor reconstruction performance, e.g., the value of pixels of the prediction can beyond a range of 0 to 255 through the linear combination of hypothesis set. To address this problem, we present a resample-based hybrid multi-hypothesis scheme for block-based DCVS.

The background of our research is to implementing WVSNs for real-time field environmental monitoring when having limited computing capacity. Considering its acceptable performance and low computational complexity, we expand the method [1] to present our scheme. The main difference between the method [1] and our proposal is that, further considering the JL lemma [7], we integrate the measurement of SI into method [1] while taking the influence of the accuracy of SI into account.

2. Proposed Scheme

The proposed resample-based hybrid multi-hypothesis (RH-MH) scheme is shown in Fig. 1. The dotted part is the traditional scheme of multi-hypothesis (MH) reconstruction [1] and the shadow parts are the innovations we mentioned above. In MR-MH reconstruction, side information (SI) x_{si} generated from the reconstructed key frames x_{key} is not only used to generate hypothesis set H_i, but also integrated into the original measurements of non-key frames y_i for MH reconstruction. Next, to prevent the deterioration in reconstruction quality caused by integrating side information, we mix multiple multi-hypothesis reconstructions adaptively by resampling each reconstruction in H-MH reconstruction. Finally, we output the reconstructed non-key frames.

2.1 Multi-Hypothesis Reconstruction Based on Measurements Reorganization (MR-MH)

The JL lemma [7] states that, as long as $M \geq \mathrm{O}(\log L)$, a set of L points in an N-dimensional space can be embedded into an M-dimension subspace in such a way that distances

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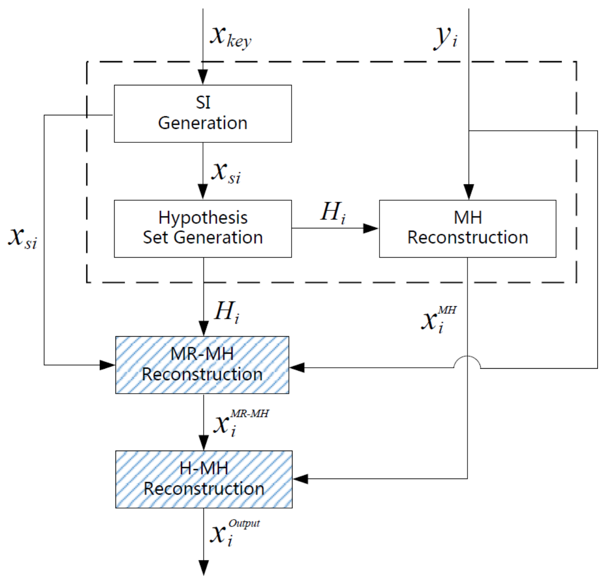

Fig. 1 Proposed RH-MH scheme for DCVS.

between the points are nearly preserved. However, it is incapable to set M by calculating exact low bound given L points. As a sequence, the multi-hypothesis prediction is likely inaccurate at a low sampling rate $r = M/N$. To address this problem, there are two main ideas: (1) decrease L, which means decreasing the number of hypothesis set; (2) increase M, which means increasing the number of measurements. However, the former solution cannot guarantee an improved prediction because the decrease of L can result in a reduced ability to represent each block, which can lead to poor reconstruction quality. Hence, we choose the later solution by integrating SI into the original measurements based on the fact that increasing M can improve the accuracy of prediction with high probability, which is the main difference between the proposed method and method [1]. First, we resample SI with a sampling rate $r_{si} = M_{si}/N$ as:

$$y_{si,i} = \varphi_{si} x_{si,i} \tag{1}$$

where $x_{si,i} \in R^{N\times 1}$ indicates the i-th block of x_{si}, $\varphi_{si} \in R^{M_{si}\times N}$ refers to the measurement matrix of $x_{si,i}$, and $y_{si,i} \in R^{M_{si}\times 1}$ denotes the measurements of $x_{si,i}$. Then, we reorganize $y_{si,i}$ into the original measurements $y_i \in R^{M\times 1}$ as:

$$Y_i = [y_i; y_{si,i}] \tag{2}$$

where $Y_i \in R^{(M+M_{si})\times 1}$ denotes the reorganized measurements whose sampling rate is increased from r to $r + r_{si}$. The MR-MH reconstruction is described as followed:

For each block i

$$w_i^{MR-MH} = \arg\min_w \left\|Y_i - [\varphi; \varphi_{si}]\, H_i w\right\|_2^2 + \lambda \left\|\Gamma w\right\|_2^2$$

$$\overline{x_i^{MR-MH}} = H_i w_i^{MR-MH}$$

$$x_i^{MR-MH} = \overline{x_i^{MR-MH}} + \text{Reconstruct}(Y_i - [\varphi; \varphi_{si}] H_i w_i^{MR-MH}, [\varphi; \varphi_{si}])$$

End

Output x_i^{MR-MH}

where $\varphi \in R^{M\times N}$ denotes the measurement matrix of the original signal at decoder, H_i indicates hypothesis set of i-th block which are generated by stacking (column-wise) a number of vectorized blocks of SI that are lying inside the search window [6], λ is a non-negative real value parameter, Γ is a Tikhonov regularization matrix [1] and Reconstruct(.) is SPL algorithm [1] to recover the signal. It's noted that, although integrating SI into the original measurements can improve the accuracy of multi-hypothesis prediction with high probability, the inaccuracy of SI can also have a negative effect on reconstruction quality. Different from method [1], we further take the influence of the accuracy of SI into account. Hence, instead of assigning r_{si} to the maximum sampling rate allowed $1 - r$, we find out that a value of $r_{si} \in [0.1, 0.3]$ provided best results; consequently, we set $r_{si} = 0.1$.

2.2 Hybrid Multi-Hypothesis Reconstruction (H-MH)

To further prevent the deterioration in reconstruction quality caused by SI, besides setting a low r_{si} in MR-MH reconstruction, we also conduct normal multi-hypothesis (MH) reconstruction to get a reconstructed non-key frame x_i^{MH} in the meantime and then carry out H-MH reconstruction in which we mix multiple multi-hypothesis reconstructions adaptively by resampling each reconstruction.

In H-MH reconstruction, we resample each block x_i^{MR-MH} and x_i^{MH} with the same sampling rate of the original signal r:

$$y_i^{MR-MH} = \varphi x_i^{MR-MH} \tag{3}$$

$$y_i^{MH} = \varphi x_i^{MH} \tag{4}$$

and calculate each Euclidean distance with the original measurements y_i to choose the final reconstruction of i-th block x_i^{Output}. Criterion is as followed:

$$x_i^{Output} = \begin{cases} x_i^{MR-MH}, & \left\|y_i - y_i^{MR-MH}\right\|_2 < \left\|y_i - y_i^{MH}\right\|_2 \\ x_i^{MH}, & \left\|y_i - y_i^{MR-MH}\right\|_2 \geq \left\|y_i - y_i^{MH}\right\|_2 \end{cases} \tag{5}$$

Next, we output the final reconstructed non-key frame x^{Output} by reorganising each reconstructed block x_i^{Output}.

3. Results

Compared with MH-BCS-SPL algorithm [1], which is known as the state-of-the-art algorithm in block-based DCVS, several experiments have been conducted to evaluate the performance of our proposed scheme. In both schemes, we set a group of pictures $GOP = 2$, the size of block $B = 16$. We use the Gaussian random matrix as the measurement matrix and the DDWT basis as the sparse basis matrix in SPL algorithm for both intra-frame MH-BCS-SPL algorithm in key-frame recovery and the proposed method in non-key-frame recovery. For a fair comparison, other parameter settings are the same as [1]. The bilateral motion compensation algorithm [8] is used to generate side information for each non-key frame. Each key frame is sampled with a rate $r = 0.7$ while each non-key frame with a rate varying between 0.1 and 0.3. In this letter, Hall sequence, Coastguard sequence and Container sequence (frame size: 352×288; Frame number: 300) are used as test sequences, and the average Peak Signal to Noise Ratio (PSNR) of all non-key frames as an objective standard to measure reconstruction performance.

The results of Hall, Coastguard, and Container sequence are depicted in Fig. 2. The reconstruction performance with the proposed scheme is obviously better than that with MH-BCS-SPL at a low sampling rate. Take Hall as an example, comparing with MH-BCS-SPL, there is a 1.5dB increase in PSNR with a subrate of 0.1. Experiments with single MR-MH reconstruction are also conducted, in which we find that there exists a deterioration in reconstruction quality at a high subrate. The reason is that the original measurements are enough for a guaranteed reconstruction and SI can be seen as noise when subrate is high. However, the deterioration can be effectively prevented with H-MH reconstruction. It is worth pointing out that the proposed RH-MH scheme is suitable for real-time video sensing because it conducts MR-MH reconstruction and MH reconstruction in the meantime and doesn't need extra reconstruction time.

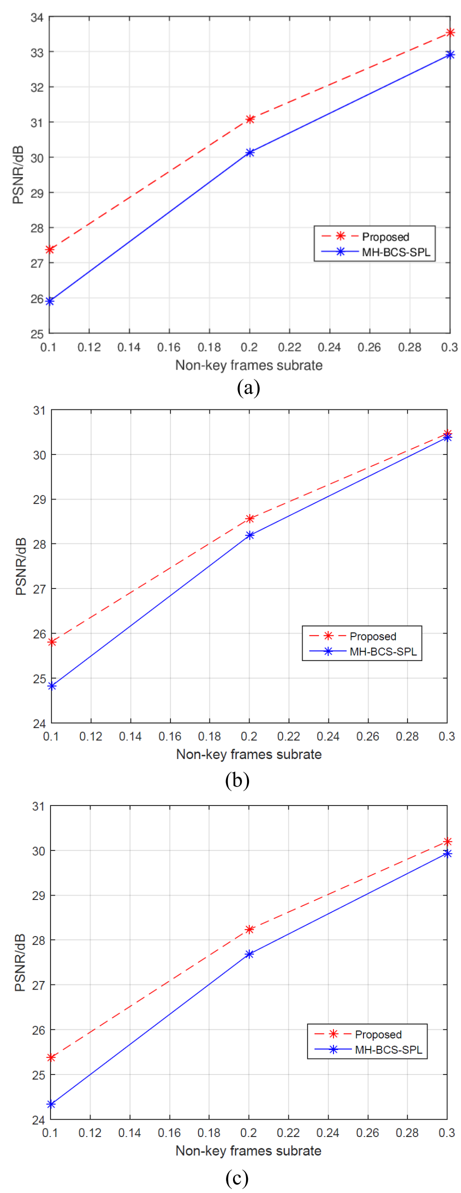

Fig. 2 Reconstruction performance of the proposed scheme. (a) Hall sequence; (b) Coastguard sequence; (c) Container sequence.

4. Conclusion

The accuracy of prediction guarantees good reconstruction performance in multi-hypothesis prediction technique. However, a low sampling rate can lead to inaccurate prediction. To address this problem and enhance the reconstruction quality of non-key frames, we present a resample-based hybrid multi-hypothesis (RH-MH) scheme for block-based distributed compressive video sensing. Experimental results have manifested that, the proposed scheme outperforms the state-of-the-art technique at the same low sampling rate and can be effectively applied into WVSN.

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