Adaptive Sampling Rate Allocation Based on Image Entropy for Block-Based Compressed Sensing of Video

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Abstract. The traditional block-based compressed sensing (BCS) of video is measured at a fixed sampling rate. In these schemes, when the video is reconstructed, the block effect occurs due to the spatial redundancy of the image. To solve this problem, we proposed the image entropy as allocation condition of sampling rate for each block. This method calculates the entropy of the difference between the key frames and the non-key frames. Simulation results show that the proposed method has superior performance of the reconstructed video and subjective vision in comparison to the adaptive scheme based on variance and the time of reconstruction is also reduced.

Introduction

In recent years, there has been a great deal of interests in compressed sensing (CS) with the signal recovered without distortion\textsuperscript{(1)}. Image acquisition equipments based on CS as compressive imaging (CI) have been produced out to reduce the cost\textsuperscript{(2)}. Compressed sensing of video is faced with a number of problems, including large computational burden of reconstruction and high storage of random measurement matrix. We use BCS to reduce the cost of random measurement. BCS uses the same measurement matrix to sample each block. However, in the block method, each image block has the same sampling rate, ignoring the different characteristics of each block. In order to overcome this defect, we use the variance of block to measure the details of the complexity and set different sampling rate of each block\textsuperscript{(3)}. However, it is necessary to obtain the original digital image firstly for calculating the variance of the image block, which seriously deviates from the basic spirit of CS while compressing the image directly.

In this paper, we propose a new adaptive sampling rate setting method to adaptively set the sampling rate of blocks. In this method, the sampling rate is allocated adaptively according to the entropy calculated with the measured value of the pre-sampling.

Image Entropy

In the adaptive block compressed sensing (ABCS) framework, variance is used as a measurement condition. Image entropy is a statistical form of characteristics, which reflects the amount of information in the average amount of the image. The neighborhood gray value of the image is chosen as the spatial feature of the gray scale distribution and is composed with the pixel of the image to a characteristic bigram, which is denoted as \((i, j)\), where \(i\) denotes the gray value of the pixels \((0\leq i\leq 255)\) and \(j\) denotes the neighborhood gray scale mean \((0\leq j\leq 255)\).

\[ P_{ij} = f(i, j) / N^2 \]  

(1)

The above Eq. 1 can reflect the comprehensive characteristics of the gray value between a certain pixel and the surrounding pixels, \(f(i, j)\) is the frequency of the characteristic bigram \((i, j)\) appears, \(N\) is the scale of the image. Then the discrete two-dimensional entropy of the image is formulated as
\[ H = \sum_{i=0}^{255} p_{ij} \log p_{ij} \]  

(2)

We select the images with the size of 512×512, the measured value distribution of the variance (Var=0.506) and information entropy (Ent=7.832) of images.

In Fig. 1, the difference in entropy distribution of image blocks is more obvious than the variance, and the data difference is bigger. So entropy can better distinguish between complex blocks and smooth blocks and then allocate the corresponding sampling rate. In this paper, we use the information entropy of image block to optimize the sampling and make a better performance on the gathering condition of the information of image block.

**Adaptive Sampling Rate Allocation of Video Framework**

In this paper, the information entropy is used to identify the image block pixel distribution and optimize the sampling in block-based distributed compressive video sensing (DCVS) framework shown in Fig. 2.

In the encoder end, the video sequence is divided into key frames and CS frames independently. In order to make the encoding simpler, we use the block-based random sampling for both key and CS frames. Key frames are adopted a fixed high sampling rate. CS frames combine with key frames’ information of reconstruction and are adopted a lower dynamic and adaptive sampling rate. In the decoder end, the key frames are reconstructed directly with the CS reconstruction algorithm. For CS frames, we use the prediction (side information) generated by the reconstructed key frame to joint reconstruct. The framework is a DCVS framework with feedback information.
Adaptive Sampling Rate Allocation Based on Entropy

Key frames have the information for the following CS frames, so we use a fixed block sampling rate in this paper. The sampling rate for the key frame is $a$ and the pixel of each frame is $N$, then the total number of sampling is known as $M = a \times N$.

The difference represents the temporal relevance of image, and the entropy represents spatial correlation. For CS frames, since the key frames have been previously decoded and reconstructed, we can perform the entropy processing on the difference between the key frames and CS frames. The total sample rate is preset consistently with the key frame in advance. The total sampling number is $M$, pre-sampling rate is $d$ ($a > d$) and the sum of all blocks’ adaptive sampling rate is $(a-b)$.

We set $Y$ as the reconstruction matrix of the key frames and $X$ as the pre-sampling matrix of the CS frames, and the dimension of $X$ is $M'$.\[ \begin{align*}
U' &= Y - X \quad (M' = d \times N) \\
U' \text{ in Eq. 3 represents the changes of gray value. As the difference between the range } &(-256, 256), \\
\text{the Eq. 4 } &U = U' + 256
\end{align*} \]

\[ U = U' + 256 \] ensures that we can do hash to the data and get the probability of the change of pre-sampled pixels for each measurement domain. The information entropy of frame block $k$ in the measurement domain as $U = U' + 256$

\[ h(k) = \sum p_{ij} \log p_{ij}. \]

The number of measurements in per block is formulated according the proportion of the entropy of each piece to the sum of all the entropy values as

\[ M_i = M' + \frac{h(k) \times (a-d) \times N}{\sum h(k)}. \]

We set the maximum number of sampling times for the block as $upper = 0.9B^2$ and limit the number of measurements beyond the upper bound to the upper value, and then distribute the remaining of measurements evenly to the unbounded blocks. After the allocation, the measures of some blocks may be out of bounds again, and the above steps are repeated until all the blocks are not over the border. Then the final measurements can be obtained.

The measured values of each block will be transmitted to the decoder end after finishing the processes above, and then we use the appropriate CS reconstruction algorithm to reconstruct the frame blocks. The value of the measurement is often larger to ensure the accuracy of the variance of the samples. Therefore, this scheme will increase a little of the computational complexity than traditional scheme.

Simulation Results

In order to test methods of the adaptive sampling rate proposed in this paper, we compare two methods: (1) non-adaptive method, that is, key frame and CS frame are using fixed sampling rate compressed sensing mode\[^5\]. (2) Using variance as a CS frame allocation rate of the conditions mentioned in [3]. Then we adopt the adaptive sampling rate for each frame according to the method in this program and reconstruct key and CS frames respectively with the GPSR algorithm. We use daubechies9/7 wavelet as sparse vector. We adopt the structural random Hadamard matrix (SRHM) as the stochastic measurement matrix to be more hardware-friendly\[^6\]. Boat and football’s first 50 frames as test sequence frames are in the CIF format ($352 \times 288$) standard. The boat sequence is slow movement and football sequence is violent movement. Even frames of boat sequence and odd
frames of football sequence are CS frames. We take the average of 5 measurements of peak signal to noise ratio (PSNR) of reconstructed CS frames.

![Frame Comparison](image)

(a) Original frame (b) Non-adaptive frame (29.26dB) (c) Variance adaptive frame (30.26dB) (d) This program (31.23dB).

Fig. 3 shows the subjective visual quality comparison of the 59th frame of the football sequence by each scheme at the total sampling rate of 0.7 and the pre-sampling rate of 0.4. It can be clearly seen that the adaptive scheme proposed in this paper can effectively alleviate the block effect and obtain superior subjective viewing performance compared with the non-adaptive scheme. The PSNR value of this paper’s adaptation program is increased by 0.97db.

<table>
<thead>
<tr>
<th>samples</th>
<th>methods</th>
<th>the pre-sampling rate</th>
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<tbody>
<tr>
<td></td>
<td>0.2</td>
<td>0.3</td>
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<tr>
<td>boat</td>
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<tr>
<td></td>
<td>Variance adaptive</td>
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<td></td>
<td>proposed</td>
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<tr>
<td>football</td>
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<td>22.43</td>
</tr>
</tbody>
</table>

Table 1 tabulates the PSNR results of three schemes on reconstructed CS frames. For the proposed methods, the total sampling rate is fixed to 0.7. The adaptive sampling methods can effectively improve the objective quality of reconstructed frames compared with non-adaptive method. In this paper, the PSNR results of proposed scheme are yield about 1dB improvement for the boat sequence. This is mainly because after adaptive adjusting the total preset sampling rate, the number of sampling on each block can guarantee a good quality of reconstruction. For football sequence, the PSNR values are generally lower than that of the boat sequence. In my opinion, the
more intense the sequence moves, the less pixel information of key frame can provide for CS frames. The less the pre-sampling information is obtained when the pre-sampling rate is low, the greater the impact on allocating subsequent rate. As the pre-sampling rate increases, the more information we get from each block, the more reasonable allocation on sampling rate and then PSNR values increase faster. Therefore, the pre-sampling rate should be sufficient to reduce the error between the true value and the sampled value and ensure the effectiveness of the program.

Summary

In this paper, we present an adaptive sampling rate allocation scheme, aiming at the existing traditional block compressed sensing and variance-based adaptive compressed sensing algorithms. We allocate CS frame sampling rate with the information entropy of the pre-sampled frames. Simulation results show that the CS frames reconstructed by our scheme is of higher quality on subjective vision. The use of the hash algorithm makes the algorithm complexity lower than the variance-based scheme.

There are still shortcomings that future work should consider. In this paper, the improvement of PSNR values is worthy of increasing the amount of calculation. So only when the pre-sampling rate is large enough, the error between pre-sampled and the original information can be reduced. Therefore, how to shorten the measurement time and analyze the relationship between the pre-sampling rate and the error to properly set the pre-sampling rate are also worthy of further analysis.

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