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Compressed sensing image reconstruction using intra prediction

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ABSTRACT

Compressed sensing (CS) provides a general signal acquisition framework that enables the reconstruction of sparse signals from a small number of linear measurements. In this article we present a CS image reconstruction algorithm using intra prediction method based on block-based CS image framework. The current reconstruction block is firstly predicted by its surrounding reconstructed pixels, and then its prediction residual will be reconstructed. Because the sparsity level of prediction residual is higher than its original image block, the performance of our proposed CS image reconstruction algorithm is significantly superior to the traditional CS reconstruction algorithm. Furthermore, total variation model is also used to suppress the blocking artifacts caused by intra prediction and measurement noise. Experimental results also show the competitive performance with respect to peak signal-to-noise ratio and subjective visual quality.

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1. Introduction

Compressed sensing theory is an emerging framework that permits, under some conditions, compressible signals can be sampled at sub-Nyquist rates through non adaptive linear projection onto a random basis while enabling exact reconstruction at high probability [1,2]. Moreover, signals that can be well approximated by sparse representation, such as discrete cosine transform (DCT), wavelet transform or a trained dictionary, can be sensed at a much lower rate than double their actual bandwidth, as required by the Shannon-Nyquist sampling theory [3].

Compressed sensing (CS) theory mainly relies on two fundamental principles [4,5]: sparsity and incoherent. Let $x \in \mathbb{R}^n$ be an arbitrary compressible signal and let $\Psi = [\varphi_1, \cdots, \varphi_n]$ an sparse basis or dictionary in $\mathbb{R}^n$,

$$x = \sum_{i=1}^{n} \varphi_i \theta_i = \Psi \Theta \tag{1}$$

where $\Theta = [\theta_1, \cdots, \theta_n]^T$ is the vector of sparse coefficients that represent signal x on the basis Ψ. A signal is to be said sparse or compressible if most of the coefficients in Θ are zero or they can be discarded without much loss of information. Let $\Phi = [\phi_1, \cdots, \phi_N]^T$ be $M \times N$ measurement matrix, with $M \ll N$, such that $y = \Phi x$ is $M \times 1$ vector. This is an underdetermined function, that is to say, given the observation y, there are a number of x which can satisfy the equation $y = \Phi x$. However, CS theory states that if the measurement matrix Φ and sparse basis Ψ are incoherent and their product satisfies the Restricted Isometry Property (RIP) of order-k for all k-sparse vectors for a small isometry constant δ_k, that is,

$$(1-\delta_k)||\Theta||^2 \le ||\Phi \Psi \Theta||^2 \le (1+\delta_k)||\Theta||^2 \tag{2}$$

The sparse coefficients Θ can be accurately reconstructed through the following constrained optimization problem [4]

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} ||\Theta||_{\ell_1} \ s.t. \quad y = \Phi \Psi \Theta \tag{3}$$

Afterwards, the signal x can be reconstructed by

$$\hat{x} = \Psi \hat{\Theta} \tag{4}$$

In most practical application, the signal x is not absolutely sparse or the measurements y may be corrupted by noise or quantization process. Then, the CS reconstruction procedure should be reformulated as

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} ||\Theta||_{\ell_1} \ s.t. \quad y - ||\Phi \Psi \Theta||_{\ell_2} < \varepsilon \tag{5}$$

Based on the convex optimization theory [6], the optimization problem (5) can be solved by the following unconstrained Lagrangian formulation

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \lambda ||\Theta||_{\ell_1} + (1/2)||y - \Phi \Psi \Theta||_{\ell_2}^2 \tag{6}$$

where λ is a regularization parameter which tradeoffs the sparsity level and the data fidelity. Typical methods for solving the problem in form (6) include basis pursuit denoising (BPDN) and gradient projection algorithms (GPSR) etc [7]. The final reconstruction signal is $\hat{x} = \Psi \hat{\Theta}$.

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CS theory performs acquisition and compression simultaneously, and shifts almost all computation burdens to the decoder, resulting in a low-complexity encoder. It is very suitable for image or video application [8], where the computational resource and power is limited, such as low powerful wireless multimedia sensor network or handheld multimedia acquisition terminal [9]. In this article, we will investigate the CS reconstruction algorithm based on the observation that the sparsity level of prediction residual is higher than the original pixels, so the reconstruction performance with our proposed algorithm is improved as compared with the traditional ones.

In addition, CS theory can also be used as classification and recognition tools in computer vision, especially human face recognition and palmprint recognition [10–17]. Its basic idea is to cast recognition as a sparse representation problem through new mathematical tools from compressed sensing and L1 minimization.

The rest of the article is organized as follows. Section 2 introduces some classical CS reconstruction algorithms in image application domain. In Section 3, our proposed compressed sensing image reconstruction algorithm is described in detail, including the framework of our proposed algorithm, intra prediction mode and deblocking and denoising postprocessing. Section 4 presents the experimental results and conclusions are given in Section 5.

2. Compressed sensing for images

In recent years, there has been significant interest in compressed sensing theory for image application. The most well-known case is the so-called "single-pixel camera", which is a still image acquisition device developed by Rice University [17]. The most straightforward implementation of CS on 2D images is to recast the 2D array image as a 1D vector by some predefined scanning orders. For an $N \times N$ image, it will be formed a $N^2 \times 1$ vector. In this context, the sparsity transform Ψ is a $N^2 \times N^2$ matrix consisting of N^2 basis, the memory required to store this matrix grows very fast as the number of pixels in the image increases. In order to reduce the memory requirement, a block-based compressed sensing (BCS) framework was proposed in [18,19] for 2D images. That is, an image is divided into $B \times B$ non-overlapping blocks and every block is sensing measured independently. In this case, the sparsity matrix Ψ and sensing measurement matrix Φ for the whole image can also be written in a block-diagonal form as follows

$$\Psi = \begin{bmatrix} \varphi_B & & & \\ & \varphi_B & & \\ & & \ddots & \\ & & & \varphi_B \end{bmatrix} \quad \phi = \begin{bmatrix} \phi_B & & & \\ & \phi_B & & \\ & & \ddots & \\ & & & \phi_B \end{bmatrix} \tag{7}$$

The sensing measurement procedure for image block x_j is as follows

$$y_j = \phi_B x_j \tag{8}$$

where y_j is the measurement vector of image block x_j. In our proposed algorithm, the BCS framework is also used in the experiments due to its simplicity and high efficiency.

It is well known that the sparsity level of signal x decides the quality of reconstruction signal. In general, more sparsity signal x is, more high quality the reconstruction signal is. So as to improve the sparsity level of image signal, it is proposed that, instead of seeking sparsity in the image transform domain, the total variation (TV) model is used in CS image reconstruction in [20] as follows

$$\hat{x} = \underset{x}{\operatorname{argmin}}\ ||x||_{TV} + \lambda ||y - \Phi x||_2 \tag{9}$$

However, the TV model possesses some undesirable properties, such as the staircase effect.

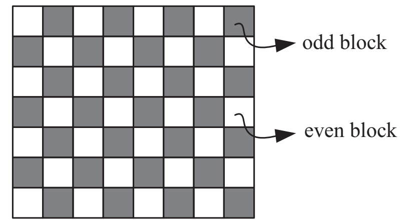

Fig. 1. Non-overlapping image blocks in checkerboard pattern.

In this article the sparsity level of reconstruction image will be enhanced by our proposed intra prediction algorithm which will be detailed in the next section. Based on the traditional image coding theory, if the current image block can be efficiently predicted, the prediction residual can be more compressed than the original image block in some transform domains [21,22], such as DCT. In other words, the sparsity level of prediction residual is higher than original block.

Let x_{pred_j} be the prediction of image block x_j, the compressed sensing measurement of its prediction residual is

$$y_{resi_j} = \phi_B \left(x_j - x_{pred_j} \right) = \phi_B x_{resi_j} \tag{10}$$

That is

$$y_{resi_j} = y_j - \phi_B\, x_{pred_j} \tag{11}$$

If the best prediction x_{pred_j} can be found, the prediction residual x_{resi_j} can also be accurately reconstructed through y_{resi_j} and the final reconstruction result $\hat{x}_j$ is calculated by $\hat{x}_j = x_{pred_j} + x_{resi_j}$. Because the prediction residual x_{resi_j} is much sparser than the original image x_j, the reconstruction accuracy of image block x_j is also higher.

3. Proposed CS image reconstruction algorithm

3.1. Framework of our proposed CS image reconstruction algorithm

In our proposed method, the image is divided into non-overlapping blocks for compressed sensing measurement as the above BCS framework. Although every image block x_j can be reconstructed by the measurement vector y_j independently based on the general sparsity basis DCT or DWT, the quality of reconstruction image can be further improved by integrating our proposed intra prediction in the reconstruction procedure, as shown in Fig. 1.

In traditional video coding standard, such as H.264/AVC [22], intra prediction is an important coding tool to improve the compression efficiency. Its basic idea is to use reconstructed pixels, including the left and the above neighbor pixels, to predict the current coding block, and finally the best prediction mode is selected by rate distortion optimization (RDO) theory. However, the original image block is not available in the CS reconstruction procedure, so it is impossible to directly select the best prediction mode in original pixel domain by RDO theory. In our proposed method, the best intra prediction mode is selected in compressed sensing domain. Let $x^k_{pred_j}$ be prediction block by the *kth* prediction mode and $\hat{x}_j$ is the reconstruction block by straightforward reconstruction algorithm, the best mode *kb* is selected by the following function

$$kb = \min_k \left|\left| x^k_{pred_j} - \hat{x}_j \right|\right|^2 \tag{12}$$

Algorithm 1. Compressed Sensing Image Reconstruction

Require: ϕ_B, Y
Output: X

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