A wavelet-based non-linear acquisition strategy for single pixel camera acquisitions

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Abstract - **Single pixel imaging opened the door to a cheaper camera architecture able to operate in a wide spectral range. We propose a new acquisition strategy for such an optical setup. Our technique obtains an image in the wavelet domain with a progressive non-linear acquisition. With a good spatial resolution, this method based on wavelet's compression can be used in fluorescence imaging to observe biological structures.**

Index Terms - ***Image Processing, Optical Imaging***

I. INTRODUCTION

The single pixel camera (SPC) architecture is the key to building small, cheap and efficient sensors. Compared to CCD or CMOS cameras architecture, SPC has several advantages. This imaging technique can indeed operate at different wavelengths where building CCD or CMOS can be expensive, it has a very good quantum efficiency and needs few storage memory. Our goal in this paper is to provide a new acquisition strategy for SPC acquisitions that leads to a low cost time-resolved imaging technique. One application of this method could be the observation of biological tissues via fluorescence imaging. In particular, the overall framework could benefit to optical tomography for preclinical imaging of animals [1].

II. PROBLEM AND RELATED WORK

We address the problem of recovering the image of an object acquired by a SPC, problem originally formulated in [2]. This optical setup consists of a digital micromirror device (DMD) and a single photon avalanche diode (SPAD). A DMD is composed of thousands of mirrors that can be independently tilted, hence acting as a tunable spatial filter.

A SPC acquisition consists in computing sequentially the dot product of the image and some DMD patterns. Let $\mathbf{f} \in \mathbb{R}^{N\times N}$ denote the image and $\{\mathbf{p}_i \in \mathbb{R}^{N\times N}, i = 1..I\}$, be the sequence of I DMD patterns. The measurements $\{m_i, i = 1..I\}$ can be expressed as:

$$m_i = \langle \mathbf{f}, \mathbf{p}_i \rangle \tag{1}$$

Then, the problem consists in retrieving $\mathbf{f}$ from $\{m_i\}$, knowing the patterns $\{\mathbf{p}_i\}$.

In [2], the authors used compressed sensing, i.e. random patterns, and reconstructed the image with ℓ_1-minimization. This approach is *nonadaptive*. In [3], the image is reconstructed directly, i.e.

$$\mathbf{f} = \sum_i m_i \mathbf{p}_i \tag{2}$$

and the image was acquired with an *adaptive* scheme. Some of the patterns were determined during acquisition depending on measurements already acquired. The difficulty lies not so much in recovering the image as in determining the DMD patterns.

In this paper, we consider the same type of approach since it avoids the ℓ_1-minimization that can be time consuming. In particular, we consider to obtain $\{m_i\}$ from wavelet patterns $\{\mathbf{p}_i\}$ using a non-linear acquisition strategy.

III. METHOD

III.1. Wavelet decomposition and pattern projection

Let $j = 1..J$ be the scale at which the image $\mathbf{f}$ is observed, J being the decomposition level, with $1 \leq J \leq \log_2 N = R$. The discrete wavelet decomposition of an image with the standard dyadic wavelets separates the signal into approximation and detail coefficients (horizontal, vertical or diagonal). The approximation image results from a low-pass filtering whereas the details appear with a high-pass filtering.

Given the positive constraint of the DMD patterns, Haar's wavelet was considered. It can indeed be shown that a wavelet coefficient can be obtained from a difference of two SPC measurements [3]. In practice, the patterns $\{\mathbf{p}_i\}$ given by Haar's wavelet only have 0 or 1 values and are all dilated/contracted and translated versions of one another.

III.2. Acquisition strategy

Wavelet decomposition was shown to give sparse signals, allowing one to discard many of the coefficients at the reconstruction step [4]. Hence, a sampling scheme has to be chosen to mainly acquire significant coefficients. Dai et al. [3] considered a father-children relationship which stands that a coefficient at scale j has 4 children at scale

$j-1$ [4]. Then, they employed a thresholding strategy to predict the relevant coefficients at finer and finer scales. Instead, we propose to non-linearly determine the relevant coefficients. This technique retains a number of the largest wavelet coefficients and was shown to give excellent image recovery [4].

Our strategy therefore consists in the following steps. First, we acquire the approximation of the image at scale J, which provides $n_{\mathrm{A}} = 2^{2L}$ coefficients with $L = R - J$. Then, the approximation image is one-level wavelet transformed and a given percentage p_J of the largest detail coefficients are retained. The four children of each of the retained detail coefficients are chosen for acquisition. It may be shown that the number n_J of detail coefficients acquired at scale J is given by

$$n_J = 3 \times n_{\mathrm{A}} \times p_J. \tag{3}$$

Then, we perform another non-linear approximation among the n_J details by keeping a new percentage p_{J-1} of the largest ones. As previously, the four children of the significant details will be considered for measurement. The number n_{J-1} of measured detail coefficients at $J-1$ is

$$n_{J-1} = 4 \times p_{J-1} \times n_J \tag{4}$$

Repeating the previous step until the finest scale $j = 1$ is reached, the total number of acquired coefficients is:

$$n = 2^{2L}\left[1 + 3\sum_{j=1}^{J}\left(4^{J-j}\prod_{i=j}^{J} p_i\right)\right] \tag{5}$$

The set of percentages $\mathcal{P} = \{p_1, p_2, ..., p_J\}$ controls the number of sampled coefficients over the total number of pixels (5). The latter ratio defines the sampling rate (SR). One can finally recover an image from the samples using the inverse wavelet transform.

This novel framework intrinsically links the acquisition setup and the signal processing tools. It is progressively decided the coefficients that will be the next samples based on previous measures by the SPC without knowledge of the whole wavelet transform of our image.

IV. RESULTS & DISCUSSION

The proposed acquisition strategy was simulated on several test images. With a SR as low as 10 %, our method shows efficient result on Lena as can be seen on Fig. 1. Table 1 presents the resulting PSNR for different test images. Compared to the ground truth images, the recovered versions showed no clear distortions. Results from experimental data are expected to confirm our findings.

Although the results are promising, they are not as good as a single non-linear approximation of the whole wavelet transform, which indicates that our strategy misses some of the significant coefficients. However, table 1 shows that the proposed non-linear strategy performs better than the thresholding strategy introduced in [3]. Our method also presents adaptivity in the sense that an unique set of percentages works well for several images (table 1) whereas a threshold is image-dependent.

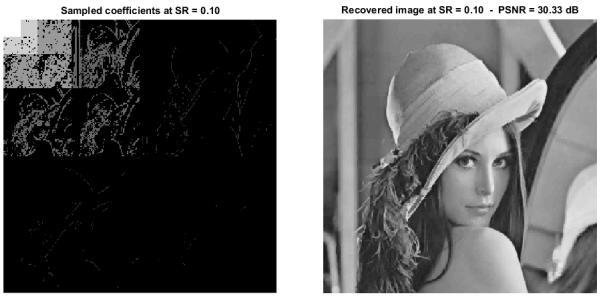

Figure 1: Results of our approach on Lena (512×512 pixels). With $\mathcal{P} = \{0.05, 0.3, 0.8, 0.95\}$ giving a SR of 10%, one can recover an image with a PSNR of 30.33 dB.

Test images	**PSNR (dB)** Non-linear	**PSNR (dB)** Threshold
Lena (512×512)	30.33	29.84
Peppers (512×512)	36.07	35.76
Cameraman (512×512)	32.32	32.05
Gold Hill (512×512)	27.83	27.70

Table 1: PSNR between ground truth images and their recovered versions. $\mathcal{P} = \{0.05, 0.3, 0.8, 0.95\}$ was used for our non-linear strategy (column 2) and for Dai's method (column 3), the threshold was chosen based on the approximation image [3]. In both cases, the SR was fixed to 10%.

V. CONCLUSION

We presented in this paper a strategy to acquire images with a SPC. Obtaining the image in the wavelet domain with a progressive non-linear approximation strategy, the method shows both good visual and numerical results. In future work, we plan to use this optical setup in fluorescence imaging to observe biological tissues.

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