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MoCS-OCT: Modified Compressive Sensing Optical Coherence Tomography with noise reduction

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Abstract

We study noise reduction using Modified Compressive Sensing Optical Coherence Tomography (MoCS-OCT). We show that averaged Modified-CS reconstruction achieves better image quality in terms of SNR, local contrast, and contrast to noise ratio (CNR), compared to the classical averaging method while reducing the total amount of data required to reconstruct the images. The same is also true when compared with standard CS based averaging method with same amount of under-sampled data.

Optical Coherence Tomography (OCT) is an optical imaging modality that has been adopted by a wide range of medical fields [1, 2]. However, due to the interferometric nature of OCT, noise reduction has long been a focus of OCT research. Various methods of speckle noise reduction have been proposed based on hardware and software to enhance the quality of OCT image [3–5]. One very successful and classical method is through averaging intensity of a series of B-scans that are successively recorded with slight lateral offset [5]. Typically, average of 10 B-scans recorded with total 300um lateral offset is sufficient to provide a satisfying high-quality image. Ubiquitous system noise is another major noise source. Averaging method is also known to efficiently reduce such system noise.

One limitation of the classical averaging method is data acquisition speed and a large data storage requirement. Because Compressed Sensing (CS) [6, 7] requires only a fraction of the total data to accurately recover image, it is becoming an increasingly popular image processing method in medical imaging. Application of CS in OCT imaging has been proposed [8–12]. In CS-OCT imaging, the reconstruction is obtained by solving the following constrained optimization problem:

$$\text{minimize } \|Wx\|_1, \text{ s.t. } \|F_u x - y\|_2 < \varepsilon \quad (1)$$

where $\mathbf{x}$ is the reconstructed signal in spatial domain; $\mathbf{W}$ is the sparsifying operator that will transform $\mathbf{x}$ to a sparse representation. If $\mathbf{x}$ itself is sparse, $\mathbf{W}$ can be the identity matrix; $\mathbf{F}$ is the under-sampled Fourier transform matrix; $\mathbf{y}$ is the measured k-space data from the scanner; and ε is the parameter controlling the fidelity of the reconstruction to the measured data, or equivalently, it is the parameter reflecting noise level. $\varepsilon \approx 0$ for noise free images. The notation $\|\mathbf{c}\|_1$ is the ℓ_1 norm, which is defined as $\|\mathbf{c}\|_1 = \sum_i |c_i|$. The objective function of the optimization problem promotes the sparsity. When 1) $\mathbf{W}\mathbf{x}$ is sparse; 2) $\mathbf{F}\mathbf{u}$ satisfies restricted isometry property (RIP) [13], CS or Basis Pursuit De-Noising (BPDN) given in Equation (1), will offer successful recovery with much fewer measurements than the Nyquist rate.

Since CS enhances signal's sparsity, it has been shown to be good at reducing noise [14]. One outstanding benefit for CS comparing to commonly used denoising methods, such as filters, is that no additional denoising procedure is needed. The noise reduction is a by-product of the reconstruction procedure.

Recently, Modified-CS [15, 16] was proposed to reconstruct a sparse signal with partially known support. If the sizes of the errors in the support are small comparing to the support size of the original signal, Modified-CS outperforms CS, particularly when the available number of measurements is too few for CS to work. Sufficient condition for exact reconstruction using Modified-CS is much weaker than those needed for CS [15]. Denote the available support knowledge by $\mathbf{T}$. Modified-CS tries to find the signal that is sparsest outside the set $\mathbf{T}$ among all signals that satisfy the data constraint, i.e. it solves

$$\text{minimize} \|(\mathbf{W}\mathbf{x})_{\mathbf{T}^c}\|_1, \text{ s.t. } \|\mathbf{F}\mathbf{u}\mathbf{x} - \mathbf{y}\|_2 < \varepsilon \quad (2)$$

here for a vector β , the notation $(\beta)_{\mathbf{T}}$ refers to a sub-vector that contains the elements with indexes in $\mathbf{T}$ and we use $\mathbf{T}^c$ to denote the complement of the set $\mathbf{T}$, w.r.t $[1, 2, \dots, n]$, n is the length of original signal. Equation (2) shows that Modified-CS minimizes ℓ_1 norm of $(\mathbf{W}\mathbf{x})_{\mathbf{T}^c}$, not the entire signal, and hence intensity of $(\mathbf{W}\mathbf{x})_{\mathbf{T}}$ is not reduced. The noise is random and usually has relatively small intensity which prevents it from $\mathbf{T}$. With non-decreased $(\mathbf{W}\mathbf{x})_{\mathbf{T}}$, the ratio of signal intensity and noise intensity is higher for Modified-CS and thus Modified-CS has better denoising effect than CS. Also, when support changes is small (which is often true [15]), with prior support information, Modified-CS has smaller error rate than CS with same sample rate without extra computation requirement and sometimes, when the sample rate is too small for CS to achieve an accurate reconstruction, Modified-CS still works.

To study Modified-CS in OCT, we used data from a spectral domain OCT (SD OCT). The details of SD OCT can be found in [9]. Reconstruction results using Modified-CS and CS on an OCT image of a mirror surface is shown in Figure 1. The first A-scan is 50% sampled and its support is used to reconstruct the second A-scan whose support will be used for generating the third A-scan. For the second and following A-scans, sample rate is 7%. Follow the same procedure until entire B-scan is reconstructed. $\mathbf{W} = \mathbf{I}$. CS used the same sampled data and reconstruction domain as Modified-CS. Since A-scans in SD OCT are

independent of each other to acquisition and reconstruction processes, Modified-CS and CS reconstruction is done on each A-scan for time control and simplicity. As we can see from Figure 1,

Modified-CS has a much smaller reconstruction error than CS. The reconstruction error for each A-scan is defined as $\| \text{reconstruction} - \text{ground truth} \|_2 / \| \text{ground truth} \|_2$. Actually, for such small sample rate, CS cannot give accurate reconstruction. It can also be inferred that supports of adjacent A-scans often change slowly. However, due to noise and complexity of OCT image, this is not always true.

The noise can be further reduced by averaging the Modified-CS reconstruction results, which takes the advantages of both averaging method and Modified-CS: Modified-CS reduces the amount of data needed for averaging method and improves image quality by increasing SNR and local contrast; averaging method which records successively B-scans at nearly identical position supplies data satisfying the requirements of Modified-CS. Due to duplicated denoising effect, Modified-CS based averaging method will reduce the noise further without influencing the signal.

Assume that the sequence of B-scans has length m and each B-scan contains l A-scans, our method consists of following steps:

1. Take fully sampled measurements for each A-scan of first B-scan; get reconstructions $\mathbf{x}_{i1}$, for $i = 1, 2, \dots, l$ by CS or conventional method; compute the $b\%$ energy-support which is defined as $T := \{k \in [1 \dots n] | x_k^2 > \zeta, \text{ or } (\mathbf{W}\mathbf{x})_k^2 > \zeta\}$ where ζ is the largest real number for which T contains at least $b\%$ of the signal energy, record as $T_1, T_2 \dots T_l$.
2. For each A-scan in the following B-scans, take the under-sampled measurement $\mathbf{y}_{ij}$ for $i = 1 \dots l, j = 2 \dots m$.
3. Solve equation (2) to get reconstruction $\mathbf{x}_{ij}$ using $\mathbf{y}_{ij}$ and T_i , for $i = 1 \dots l, j = 2 \dots m$, here $\mathbf{W}$ can be wavelet transform or identity matrix; $\mathbf{F}_u$ is the under-sampled Fourier transform corresponding to the random sample mask in step 2.
4. The final result by averaging for each A-scan is $\hat{\mathbf{x}}_i = \text{mean}(|\mathbf{x}_{ij}|)$, for $i = 1 \dots l, j = 1 \dots m$.

The size of T_i used for Equation (2) is controlled in order to satisfy requirement of Modified-CS: after step 1, if size of T_i is too big (e.g. more than 10% of signal length), the 10% largest value in $\mathbf{x}_{i1}$ will be taken to generate T_i . According to our experience, $(\mathbf{x})_T$ needs to contain at least 70% energy for a satisfying high quality reconstruction, which is usually true for SD OCT image.

To verify performance of proposed method, Modified-CS based averaging method is first applied to chicken fat image. 50% under-sampled measurements are taken for step 2. $m = 10$; $b = 85$; $\varepsilon = 60$; $\mathbf{W}$ is identity matrix; $\mathbf{y}$ is uniformly random sampled in k-domain; the size of each reconstructed A-scan is 2048. The result is compared with classical averaging method on fully sampled measurements, as well as CS based averaging method. Classical

averaging method is done by first taking fully sampled measurement for all A-scans; then applying inverse fast Fourier Transform (IFFT) to each A-scan; finally using step 4 mention above to get final result. CS based averaging method is implemented similar to Modified-CS averaging method with the same 50% under-sampled measurements. CS based averaging method replaces Equation (2) in step 3 by Equation (1) and no support is needed. The constraint optimization problem is solved using YALL1 from [17] with default parameters. Reconstruction results are shown in Figure 2. The B-scan image is cut for better display and all four images are shown in the same dynamic range.

As we can see from Figure 2, averaging results in (b),(c),(d) show that noise is reduced significantly than single frame image in (a). Result from Modified-CS based averaging method shows clearer structure and the background part for (d) is much darker than (b). The local contrast for (b) (c) (d) in Figure 2 is 5.64, 10.23 and 12.15 respectively. SNR is 17.20dB, 21.26dB and 22.48dB respectively. CNR of (b) (c) (d) is 18.30dB, 18.52dB, 19.33dB respectively.

The definition for local contrast, SNR and CNR is:

$$\text{local contrast} = \frac{\mu_o}{\mu_b} \quad (3)$$

$$\text{SNR} = 20 \times \log_{10} \left(\frac{\sqrt{\frac{1}{N_o} \sum_{(i,j) \in \text{object}} I(i,j)^2}}{\sqrt{\frac{1}{N_b} \sum_{(i,j) \in \text{background}} I(i,j)^2}} \right) \quad (4)$$

$$\text{CNR} = 20 \times \log_{10} \left(\frac{\mu_o - \mu_b}{\sigma_b} \right) \quad (5)$$

where N_o and N_b are the number of points in the object region and background region respectively. In Figure 2 and 3, area in blue rectangle is object region while the region out of it is background region, including the region cut for display. $I(i, j)$ is the intensity. μ_o and μ_b are mean of intensity of object region and background region respectively. σ_b is the standard deviation of intensity in background region.

Then we compare the methods on polymer layer phantom imaging. $m = 10$; $b = 99$; $\varepsilon = \text{norm}(\mathbf{y}) \times 0.025$; $\mathbf{W}$ is 4-level daubechies4 wavelet transform matrix; $\mathbf{y}_{ij}$ is uniformly random sampled in k-domain. The under-sample rate is 37.5%. Reconstruction result is shown in Figure 3. The B-scan is cut for better display. It can also be visually seen that Modified-CS based averaging method leads to a better image quality than classical averaging method. The local contrast for (b) (c) (d) in Figure 3 is 7.96, 7.10 and 9.40 respectively. SNR is 23.80dB, 24.68dB and 25.11dB respectively. CNR of (b) (c) (d) is 16.33dB, 16.15dB and 15.91dB respectively.

In the above two experiments, Modified-CS based averaging method reduces the storage requirement significantly comparing with classical averaging method while resulting in a better image quality. When compared to CS based averaging method, Modified-CS result

provides 1.92dB and 2.3dB improvement respectively in local contrast, 1.22dB and 0.43dB improvement respectively in SNR. It is noteworthy to mention that the improvement is stable for Modified-CS method on the local contrast and SNR compared to classical method, no matter in which domain the reconstruction is implemented, while improvement of local contrast is not guaranteed for CS method (as in Figure 3). According to experiments we have done, Modified-CS method always gives bigger improvement for local contrast and SNR than CS method. Enlarging ε will result in higher local contrast and SNR while losing more small signals. Higher energy support percentage will increase local contrast and SNR as long as the support size requirement is satisfied [15]. Larger sample rate gives slightly better local contrast and SNR while resulting in higher storage requirement and longer acquisition time. Reconstruction domain should be chosen in which the signal has sparsest representation. However, spatial domain, where local contrast and SNR are tested, usually offers higher score because the noise is reduced directly. For CNR, Modified-CS and CS does not show stable improvement. This is because the blue rectangle region also contains part of noise whose intensity is reduced by CS and Modified-CS. Thus μ_o is decreased. Since the object region of Figure 3 is bigger, μ_o is reduced more which hurts CNR. Another problem with proposed method is some small signals tend to loss because of sparsity enhancement which, though alleviated by averaging, is still an open problem associated with CS relevant methods.

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Fig. 1.
reconstruction error of each A-scan

Fig. 2.
Result of chicken fat for (a) single frame (image size 320×250) (b) classical averaging result
(c) CS based averaging result (d) Modified-CS based averaging result

Fig. 3. Result of polymer layer phantom imaging for (a) single frame (image size 480×250) (b) classical averaging result (c) CS based averaging result (d) Modified-CS based averaging result