FFOCT imaging based on compressed sensing

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Abstract. With the demand for high-resolution images, the storage space occupied by the images of the full-field optical coherence tomography (FFOCT) system is becoming more and more intensified. How to reduce the data volume of high-resolution image systems has become a research hotspot in the image processing industry. In particular, precision medicine requires high-resolution images of organs and tissues, and this data storage system requires a large storage space. For this reason, based on the high-resolution tomographic image obtained from our organ tissue, compressed sensing theory is used to perform compression reconstruction simulation. It is verified that the amount of data stored in the three-dimensional image of the diseased tissue is effectively reduced without changing the image resolution.

1. Introduction

Tomography technology can be used to study the complex internal structure of an object. Tomographic imaging could visualize the internal structure of an object, such as a floppy disk, air plastic, a casing, or a magnetic storage medium object. At present, optical coherence tomography is a research hotspot in the medical imaging world. Full-field optical coherence tomography (FFOCT) system can obtain optical tomographic images with micron resolution in three dimensions [1-2]. The key question in clinical application of FFOCT is whether it can obtain images with the same resolution as traditional pathological sections. Based on the FFOCT system developed in our lab, the high-resolution sectional images of human tissues including esophagus, intestine and uterus were obtained for the first time. However, as the resolution of the image obtained by this method is high, and this high-resolution image occupies a large storage space. How to reduce the amount of data stored in the high-resolution image system has become a research hotspot in the image processing industry. This is especially useful for precision medicine. In this paper, we have tried to solve the above problem based on compressed sensing (CS) theory [3-4].

2. The principle of compression and reconstruction

2.1. Signal sparse representation theory

Signals that are sparse or compressible under a certain transform domain are prerequisites for compressed sensing theory and are the basis for many modern signal processing theories. How to design an effective transformation base, which could make the number of projection coefficients of the signal in the dictionary less, is the premise of using CS theory to achieve signal acquisition [3-4].

Let \( x = [x_1, x_2, \cdots, x_N]^T \) be a vector, and the matrix \( A = [a_1, a_2, \cdots, a_N] \) is a transformation base. The representation of the signal \( x \) on the transformation base \( A \) is:
\[ \mathbf{x} = \sum_{n=1}^{N} s_n \mathbf{A}_n = \mathbf{As} \]  

(1)

where \( \mathbf{s} = [s_1, s_2, \ldots, s_N]^T \) is a \( N \times 1 \) weight coefficient vector. A vector \( \mathbf{x} \) is said to be sparse or compressible if the number of non-zero elements in \( \mathbf{s} \) is \( K \) or greater than \( K (K \ll N) \). At present, sparse dictionaries used to represent signals mainly include orthogonal base dictionaries and overcomplete redundant dictionaries. Commonly used orthogonal bases include Fourier orthogonal bases, short-time Fourier orthogonal bases, wavelet bases, etc. [5-6]. The sparsely decomposed signal representation theory under the overcomplete dictionary has become a hot topic in the field of signal sparse representation [7-12].

2.2. Non-correlated measurements of signals

The linear measurement of sparse signal \( \mathbf{x} \) can be expressed as:

\[ \mathbf{y} = \mathbf{\Phi x} \]  

(2)

where \( \mathbf{\Phi} = [\mathbf{\phi}_1, \mathbf{\phi}_2, \ldots, \mathbf{\phi}_M] \) is measurement matrix. Substituting (1) into (2), we can get

\[ \mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi As} \]  

(3)

Equation (3) can be abbreviated as

\[ \mathbf{y} = \mathbf{\Psi s} \]  

(4)

where \( \mathbf{\Psi} = \mathbf{\Phi A} \) is called perceptual matrix or recovery matrix. In the transformation process above, only by satisfying the restricted isometry property (RIP) [13], it is possible to recover the original signal \( \mathbf{x} \) from the observation signal \( \mathbf{y} \) through the reconstruction algorithm.

RIP guidelines are: If there is a constant \( \delta_K \in [0,1) \). For any \( \mathbf{s} \), equation (5) is established.

\[ (1 - \delta_K) \| \mathbf{s} \|_2^2 \leq \| \mathbf{\Psi s} \|_2^2 \leq (1 + \delta_K) \| \mathbf{s} \|_2^2 \]  

(5)

We say the awareness matrix or recovery matrix \( \mathbf{\Psi} \) meets the RIP criteria, and \( \delta_K \) is the constant of \( \mathbf{\Psi} \) in RIP.

Although the RIP criterion has a clear theoretical definition, it is difficult to determine whether a perceptual matrix satisfies the criterion, and it is difficult to design a measurement matrix from this criterion. In addition, the RIP criterion is a sufficient condition for signal recovery and is not a necessary condition. According to RIP guidelines, it has been found that many matrices satisfy the conditions, and an effective measurement matrix design method is also proposed. The common compression measurement matrices are: Gaussian random measurement matrix [14], very sparse projection matrix [15], sub-Gaussian random matrix [16], Bernoulli random matrix, and so on. We can use these measurement matrices to recover the signal.

2.3. Signal reconstruction algorithm

Signal reconstruction refers to the process of recovering the original signal from the compressed sampled observation signal. Signal reconstruction algorithm is the most important content of the three cores of compressed sensing theory, which directly affects the quality of the reconstructed signal and the complexity of the reconstruction. The premise of signal reconstruction is the sparse property or compressible nature of the signal. The essence is to solve the optimization problem of sparse constraints. Sparse constraints of the signal can be achieved with a minimum norm \( l_0 \). The optimization problem for directly solving the norm \( l_0 \) is an NP problem, it is difficult to solve the combination of all its signals, and even the reliability of the solution cannot be verified. Therefore, the norm \( l_0 \) is used instead of solving the norm \( l_0 \). The commonly used algorithms are: base tracking
algorithm (BP), matching pursuit algorithm (MP) [17-18], smooth norm $l_0$ method (Smoothed, SL0) [19-20] and so on. The matching tracking algorithm has less complexity and fast calculation speed, which is a very effective algorithm.

Matching pursuit algorithm is a kind of greedy algorithm. After continuous improvement, the improved matching tracking algorithms mainly include OMP algorithm, Stagewise OMP (St OMP) algorithm, Regularized OMP (ROMP) algorithm and Compressive Sampling Matching Pursuit (CoSaMP) algorithm, etc. Taking the OMP algorithm as an example, the idea of the matching pursuit algorithm is to obtain the sparse decomposition result of the signal when the convergence condition is satisfied by continuously searching for the largest correlation component between the residual vector and the measurement matrix. The idea of orthogonal matching pursuit is essential to solve K-sparse. For simplicity, assume $K = 1$, and solve the position $q$ of the unique non-zero element $y_q$ in $y$ and the column. Then iterate and find other $K$ values. Match tracking uses "greedy" ideas to find these column vectors. The residuals are selected to be orthogonal during each iteration and then subtracted from the residuals to enter the next iteration until the iteration exit condition is satisfied. The specific flow of this algorithm is as follows[13]:

- a: The initial margin is set to $r_0 = y$; the iteration number is set to $n = 1$; the index value set is $A = \Phi, J = \emptyset$;
- b: Calculate the correlation coefficient $w$, and store the serial number of the maximum value in the correlation coefficient in $J$;
- c: Update support set $\Phi_A$, where $A = A \cup J$;
- d: Get $S$ from $S = \arg\min \|Y - \Psi \cdot \hat{S}\|$, and use $r_{new} = Y - \Psi \cdot \hat{S}$ to calculate the margin;
- e: If $r_{new} - r \geq \varepsilon$, let $r = r_{new}$, and $n = n + 1$, then go to b; otherwise, the iteration is terminated.

3. Image compression reconstruction processing

In the experiment, based on the compressive sensing technology, we used the tomographic imaging results of human esophageal and intestinal cancer tissues. In the study, we used BP algorithm, OMP algorithm and StOMP algorithm respectively, the sampling rate is 0.6. When using these algorithms, the PS NR and error of the BP algorithm are better than those of the OMP algorithm and the StOMP algorithm, which shows that the compressive sensing technology can be applied to medical image processing, and the BP recovery algorithm is more suitable, which is specifically given in table 1-5. The results of compression reconstruction experiments on FFOCT imaging were performed, as shown in figure 1-5.

![Figure 1](image1.png)  
**Figure 1.** Comparison of original images and reconstructed images in the uterus cancerous region.
Table 1. PSNR and error of each algorithm.

|          | BP    | OMP   | StOMP |
|----------|-------|-------|-------|
| PSNR(dB) | 40.1828 | 36.2949 | 29.4387 |
| EROP     | 0.0388 | 0.0606 | 0.1335 |

Figure 2. Comparison of original uterus area images and reconstructed images.

Table 2. PSNR and error of each algorithm.

|          | BP    | OMP   | StOMP |
|----------|-------|-------|-------|
| PSNR(dB) | 41.0862 | 37.1882 | 30.2238 |
| EROP     | 0.0370 | 0.0580 | 0.1292 |

Figure 3. Comparison of original images of intestinal cancer area and reconstructed images.
Table 3. PSNR and error of each algorithm.

|            | BP | OMP | StOMP |
|------------|----|-----|-------|
| PSNR(dB)   | 41.4594 | 37.5752 | 30.5356 |
| EROP       | 0.0364 | 0.0569 | 0.1280 |

Figure 4. Comparison of original images of esophagus cancer area and reconstructed images.

Table 4. PSNR and error of each algorithm.

|            | BP | OMP | StOMP |
|------------|----|-----|-------|
| PSNR(dB)   | 41.8340 | 37.9266 | 30.8289 |
| EROP       | 0.0356 | 0.0559 | 0.1265 |

Figure 5. Comparison of original images of the intestinal area and reconstructed images.
Table 5. PSNR and error of each algorithm.

|         | BP     | OMP    | StOMP  |
|---------|--------|--------|--------|
| PSNR(dB)| 44.2399| 40.3470| 34.1429|
| ERROP   | 0.0410 | 0.0641 | 0.1309 |

4. Conclusion
The experimental results of compressive reconstruction studies of FFOT imaging are illustrated in this paper. When adopting BP algorithm, OMP algorithm and StOMP algorithm respectively, the PSNR and error of BP algorithm are better than those of OMP algorithm and StOMP algorithm, which shows that compressive sensing technology can be applied to medical image processing, and BP recovery algorithm is more suitable.

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