Non-invasive imaging based on sparse representation

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Abstract—In this paper, we propose a method based on sparse representation to accelerate the scanning technique to perform non-invasive imaging through scattering layers. The scanning time is proportional to the size of the collected integrated intensity pattern and it usually takes tens of hours to finish the collecting process. To speed up the scanning technique, only a much smaller integrated intensity pattern is collected. A training set of integrated intensity pattern pairs with sizes corresponding to the necessary integrated intensity pattern that makes the scanning technique work well and the much smaller one is constructed. And a pair of dictionaries is trained from the constructed set exploiting the K-SVD algorithm. Based on sparse representation, the necessary integrated intensity pattern can be recovered from the much smaller one using the trained dictionaries, thus realizing non-invasive imaging successfully. Experimental results show that our method can successfully make the scanning time reduced by 8/9 without deteriorating the imaging quality of the scanning technique.

I. INTRODUCTION

Non-invasive imaging through scattering layers is a great challenge in many fields such as life sciences and nanotechnology. Light is randomly scattered and diffused when propagating through scattering layers, making it difficult to obtain clear images of objects behind the scattering layers. Owing to the study of speckle phenomena [1] and phase retrieval algorithms [2-4], performing non-invasive imaging through scattering layers using diffused light becomes possible and great breakthroughs have been made recently. To date, two methods can be used to obtain images of objects through scattering layers non-invasively. One is the scanning technique proposed by Bertolotti et al [5] in 2012. The speckle pattern produced by the scattering layer is scanned across a fluorescence object and the resulting fluorescence back through the scattering medium is collected. Exploiting “memory effects” [6-8] of the speckle pattern and phase retrieval algorithms [2-4], a detailed image of the fluorescent object can be retrieved successfully. The other is the single-shot technique proposed by Katz et al [9] in 2014. The single-shot technique can realize non-invasive imaging through scattering layers at real-time. They illuminated the fluorescent object with spatially incoherent light that has passed through the first scattering layer and captured only one single high-resolution image of the scattered fluorescence from the back of the second scattering layer. The single scattered fluorescence image encodes sufficient information of the object and object can be retrieved from the scattered fluorescence image using phase retrieval algorithms [2-4]. Compared with the scanning technique, the single-shot technique has some obvious limitations [10]. First, the field-of-view of the single-shot imaging method is much smaller than the scanning technique and there is currently no effective way to extend it. Second, this method is only valid when the scattering layer is quite thin. If the object is hidden behind a thick scattering medium, it is impossible to retrieve the image of the object. Third, using a hole in a black screen as the fluorescent object is too ideal for a real experiment. All in all, the scanning technique is a more feasible choice to perform non-invasive imaging through scattering layers.

Though the scanning technique has noticeable advantages, there are some problems yet to be solved. For each step during the scanning process, we need to capture the scattered fluorescence image to obtain the integrated fluorescence intensity which encodes information about the fluorescent object. In order to acquire enough information, tens of thousands of scattered fluorescence images need to be gathered to form an integrated intensity pattern, thus making the scanning process sustain tens of hours. It is necessary to accelerate the imaging process when putting the scanning technique into real applications.

In this paper, we propose a method based on sparse representation [11-12] to solve the problems of the scanning technique. The scanning range of the speckle pattern is a square determined by the “memory effects” [6-8] of the scattering layer. In order to accelerate the scanning process, the scanning step size of the speckle pattern is changed to $N(N = 2, 3, 4\cdots)$ times of the necessary value and a much smaller integrated intensity pattern is collected. A training set of integrated intensity pattern pairs with sizes corresponding to the necessary integrated intensity pattern that makes the scanning technique work well and the much smaller one is constructed. And a pair of dictionaries is trained from the constructed set exploiting the K-SVD algorithm [13]. Based on sparse representation [11-12], the necessary integrated intensity pattern can be recovered from the much smaller one using the trained dictionaries. Experimental results show that our method can successfully make the scanning time reduced by $8/9$ as the scanning technique is used to perform non-invasive imaging.
The rest of this paper is organized as follows: Section 2 introduces the scanning technique of non-invasive imaging. Section 3 details our approach of non-invasive imaging based on sparse representation. Experiments and obtained results are shown and discussed in Section 4. Section 5 concludes the paper.

II. SCANNING TECHNIQUE OF NON-INVASIVE IMAGING

The working principle of speckle scanning technique is illustrated in Fig. 1 [5]. When the laser beam is normally incident on the first scattering layer and transmits through it, a speckle pattern will be produced on the fluorescent object plane. Then the fluorescence excited by the speckle pattern is scattered by the second scattering layer and collected by the CCD camera. We define the speckle pattern and the fluorescent object as \( S(x, y) \) and \( O(x, y) \). With a proportionality constant set to 1, the integrated fluorescence intensity collected by the CCD camera can be described by the integral below [5]:

\[
I(0,0) = \iint S(x, y)O(x, y)\,dx\,dy. \tag{1}
\]

When rotating the laser beam over a small angle \( \theta = (\theta_x, \theta_y) \), owing to the "memory effects" [6-8], the speckle pattern on the object plane doesn’t change but only shifts a distance \( (\Delta x, \Delta y) = (d_1\theta_x, d_1\theta_y) \). So the integrated fluorescence intensity collected is equal to [5]:

\[
I(\theta_x, \theta_y) = \iint S(x + d_1\theta_x, y + d_1\theta_y)O(x, y)\,dx\,dy. \tag{2}
\]

It is easily derived from Eq. (2) that [5]:

\[ I \ast I = (S \ast S) \ast (O \ast O), \tag{3} \]

where \( \ast \) represents autocorrelation and \( \ast \) is the convolution operator.

\[
\begin{align*}
&\text{Laser} \\
&\text{Scattering layer} \quad \text{Object} \quad \text{Scattering layer} \\
&d_1 \quad d_2
\end{align*}
\]

Fig. 1. The schematic diagram of the speckle scanning technique

Because the autocorrelation of the speckle pattern is a peak function [1], we can have [5],

\[ I \ast I \approx O \ast O. \tag{4} \]

Calculating the Fourier transform of the autocorrelation of \( I(\theta) \), we can easily obtain the Fourier modulus of the fluorescent object \( O(x, y) \) [5],

\[
\mathcal{F}\{I \ast I\} \approx \mathcal{F}\{O \ast O\} = |\mathcal{F}\{O\}|^2, \tag{5}
\]

where \( \mathcal{F}\{\} \) represents the Fourier transform. Exploiting the phase retrieval algorithms [2-4], the object can be well retrieved. Phase retrieval algorithms [2-4] are iterative algorithms. Starting from an initial guess of the object, they perform Fourier transform back and forth between the Fourier domain and object domain, and apply the measured Fourier modulus and non-negative constraints in each domain to update the estimation for the final output. Fig. 2 shows the block diagram of phase retrieval algorithms.

\[
\begin{array}{c}
\text{Non-negative} \\
\text{Constraints} \\
\text{Fourier} \text{ Modulus} \\
\text{Constraints} \\
G = |\mathcal{F}\{r\}|^2 \\
\end{array}
\]

Fig. 2. The block diagram of phase retrieval algorithms

In our experiment, the width of the laser beam \( W \) is equal to 3.133mm and the wavelength \( \lambda \) is 532nm. The distance \( d_1 \) is equal to 1.2cm and \( d_2 \) is 6mm. The range of the "memory effects" to keep significant speckle correlations is about 1" and the largest tilting angle of the laser beam is set to be \( \theta_{max} = 0.84° \). The size of the fluorescent object is 50\( \mu \text{m} \times 50\mu \text{m} \). The scanning range of the speckle pattern on the fluorescent object plane is \( 2d_1\theta_{max} \times 2d_1\theta_{max} = 350\mu \text{m} \times 350\mu \text{m} \). The angular scanning step size in the imaging process is chosen to be 0.0048° which is corresponding to 1\( \mu \text{m} \)/step on the plane of the fluorescent object. After obtaining the integrated intensity pattern \( I(\theta) \), the image of the fluorescent object can be well retrieved.

\[
\begin{align*}
&(a) \text{The fluorescent object} \\
&(b) \text{The integrated intensity pattern} \ I(\theta) \\
&(c) \text{The autocorrelation of} \ I(\theta) \\
&(d) \text{The retrieved image}
\end{align*}
\]

Fig. 3. The imaging process for the fluorescent object “S”
The scanning technique is performed to retrieve the fluorescent object “S” in Fig. 3(a). Fig. 3(b) presents the obtained integrated intensity pattern when the scanning process is finished. Fig. 3(c) shows the autocorrelation of the obtained \( I(\theta) \) according to Eq. (4). The recovered pattern is shown in Fig. 3(d) by exploiting the phase retrieval algorithms [2-4].

III. PROPOSED METHOD

Though the fluorescent object can be retrieved successfully using the speckle scanning technique, usually tens of thousands of scattered fluorescence images need to be gathered to form the integrated intensity pattern and tens of hours will be spent to complete the scanning process. In order to accelerate the scanning process, the scanning step size of the speckle pattern is changed to \( N \mu m \) \( (N = 2, 3, 4 \cdots) \) and a much smaller integrated intensity pattern is collected. A training set of integrated intensity pattern pairs with scanning step sizes corresponding to \( 1 \mu m \) and \( N \mu m \) is constructed. And a pair of dictionaries is trained from constructed set exploiting the K-SVD algorithm [13]. Based on sparse representation [11-12], the integrated intensity pattern with scanning step size \( 1 \mu m \) can be recovered from the much smaller one with scanning step size \( N \mu m \) using the trained dictionaries, thus realizing the non-invasive imaging successfully. The block diagram of our proposed method is presented in Fig. 4.

When the scanning step size of the speckle pattern is changed to \( N \mu m \) \( (N = 2, 3, 4 \cdots) \), less information about the fluorescent object is obtained and a much smaller integrated intensity pattern will be formed.

![Block diagram of the proposed method](image)

Fig. 4. The block diagram of our proposed method

![Retrieved results from integrated intensity patterns with scanning step sizes 1 \( \mu m \) and 3 \( \mu m \) for object “S”](image)

Fig. 5. The retrieved results from integrated intensity patterns with scanning step sizes 1 \( \mu m \) and 3 \( \mu m \) for object “S”

![Integ}rated intensity pattern for fluorescent object “S” with scanning step size 1 \( \mu m \); (b) is the integrated intensity pattern for fluorescent object “S” with scanning step size 3 \( \mu m \)](image)

Fig. 6. (a) is the integrated intensity pattern for fluorescent object “S” with scanning step size 1 \( \mu m \); (b) is the integrated intensity pattern for fluorescent object “S” with scanning step size 3 \( \mu m \)

Sparse representation may provide a good solution to our problem and the integrated intensity patterns with scanning step size \( 1 \mu m \) can be recovered well from the smaller ones with scanning step size \( N \mu m \) [11-12]. It can be considered that the integrated intensity patterns, as presented in Fig. 6, are composed by a large amount of image patches. As shown in Fig. 7, the core idea of sparse representation is that image patches from the integrated intensity patterns can be well represented using a linear combination of few atoms from a dictionary.

![Core idea of sparse representation](image)

Fig. 7. The core idea of sparse representation

\( P_N \) is defined as the image patch in location \( k \) from the integrated intensity pattern with scanning step size \( N(N = 2, 3, 4 \cdots) \mu m \). \( P_1 \) represents the image patch in the integrated intensity pattern with scanning step size 1 \( \mu m \). The size of \( P_1 \) is \( N^2 \) times of \( P_N \). From the core idea of sparse representation, we have,

\[
P_1^k = D_1 q_1^k, \tag{6}
\]

\[
P_N^k = D_N q_N^k, \tag{7}
\]

where \( D_1, D_N \) are dictionaries and \( q_1^k, q_N^k \) are sparse vectors, respectively. For patches \( P_1^k \) and \( P_N^k \), it can be easily obtained that,

\[
P_N^k = L P_1^k. \tag{8}
\]
In Eq. (7), $L$ is a spatially independent operator that extracts elements in $P_N^k$ from $P_1^k$. Based on the above derivations, we can conclude that,

$$P_N^k = LP_1^k = LD_1 q_N^k. \quad (9)$$

It is obvious that $P_N^k$ can be represented by the same sparse vector, $q_N^k = q_T^k$, over an effective dictionary $D_N = LD_1$.

A training set of integrated intensity pattern pairs with scanning step sizes $1 \mu m$ and $N \mu m$ has been collected. Pairs of matching patches $\{P_1^k, P_N^k\}$ can be extracted from the set of integrated intensity pattern pairs. Applying the K-SVD algorithm [13], the dictionary $D_N$ and sparse vectors $\{q_N^k\}$ can be obtained by solving the optimization problem below,

$$D_N, \{q_N^k\} = \arg\min_k \sum \|P_N^k - D_N q_N^k\|_2$$

s.t. $\|q_N^k\|_0 \leq r \forall k, \quad (10)$

where $r$ represents the sparsity of $q_N^k$. The dictionary $D_1$ can be directly obtained from the solution of optimization problem in (11),

$$D_1 = \arg\min_k \sum \|P_1^k - D_1 q_1^k\|_2^2$$

s.t. $q_1^k = q_N^k. \quad (11)$

The obtained dictionaries $D_1$ and $D_N$ can help us to retrieve the lost information in the integrated intensity pattern with scanning step size $N \mu m$ compared with the one with scanning step size $1 \mu m$. Each patch $P$ of a new integrated intensity pattern with scanning step size $N \mu m$ can be represented by the dictionary $D_N$. The sparse vector $q$ can be obtained by solving the problem in (12),

$$\min \|q\|_0 \quad \text{s.t.} \|D_N q - P\|_2^2 \leq \varepsilon. \quad (12)$$

Exploiting the sparse vector $q$, the patch in the integrated intensity pattern with scanning step size $1 \mu m$ can be reconstructed by $D_1 q$. After all patches reconstructed, the whole integrated intensity pattern with scanning step size $1 \mu m$ is recovered. We can retrieve the fluorescent object from the recovered integrated intensity pattern successfully. Fig. 8 shows the retrieved result of fluorescent object “S” from the recovered integrated intensity pattern which is reconstructed from the integrated intensity pattern with scanning step size $3 \mu m$.

![Fig. 8. The retrieved result of fluorescent object “S” from the recovered integrated intensity pattern which is reconstructed from the integrated intensity pattern with scanning step size $3 \mu m$](image)

**IV. EXPERIMENTAL RESULTS**

An appropriate training set of integrated intensity pattern pairs with scanning step size $1 \mu m$ and $N \mu m$ need to be constructed to obtain the dictionaries $D_1$ and $D_N$. The performance of our proposed method is presented and analysed.

**A. The training set**

When applying the scanning technique to perform non-invasive imaging, phase retrieval algorithms [2-4] are required to recover the fluorescent object from its integrated intensity pattern. A specific assumption needed for the phase retrieval algorithms [2-4] is that the object must be positive and compact. In order to construct an appropriate training set, we select $96$ compact fluorescent objects to obtain the integrated intensity pattern pairs with scanning step sizes $1 \mu m$ and $N \mu m$. The $96$ compact fluorescent objects include geometric patterns, characters, Chinese words, signs and biomedical cells and they contain a lot of structures. Some of the selected fluorescent objects are presented in Fig. 9.

![Fig. 9. Some fluorescent objects to obtain the integrated intensity pattern pairs in the training set](image)

After obtaining the integrated intensity pattern pairs for the $96$ fluorescent objects, we can train the dictionaries $D_1$ and $D_N$ exploiting the K-SVD algorithm [13].

**B. The reconstruction performance**

The average reconstruction performance for the $96$ integrated intensity patterns with scanning step size $N \mu m$ in the training set has been shown in Fig. 10.

![Fig. 10. The average reconstruction performance for the $96$ integrated intensity patterns with scanning step $N \mu m$ in the training set](image)

As we can see in Fig. 10, the average PSNR of the reconstructed integrated intensity patterns becomes lower when the scanning step is larger. When performing non-invasive imaging, we need to retrieve the fluorescent objects from the reconstructed integrated intensity patterns using
phase retrieval algorithms [2-4] and the success of non-invasive imaging through scattering layers depends on quality of the retrieved objects. For several testing fluorescent objects presented in Fig. 11, the integrated intensity patterns with scanning step \(N_{\mu m}\) have been collected and the integrated intensity patterns with scanning step size 1\(\mu m\) have been reconstructed based on the dictionaries \(D_1\) and \(D_N\). The retrieved objects from the integrated intensity patterns with scanning step size \(N_{\mu m}\) and reconstructed integrated intensity patterns with scanning step size 1\(\mu m\) via phase retrieval algorithms [2-4] are presented in Fig. 12 and Fig. 13.

The retrieved objects from the original integrated intensity patterns with scanning step size 1\(\mu m\) via phase retrieval algorithms [2-4] are showed in Fig. 14.

As we can see in Fig. 13 and Fig. 14, when the scanning step size is 2\(\mu m\) or 3\(\mu m\), the quality of the retrieved objects from the reconstructed integrated intensity patterns is almost the same with that of the retrieved objects from the original integrated intensity patterns. When the scanning step size becomes 5\(\mu m\), it is almost unable to retrieve the fluorescent objects from the reconstructed integrated intensity patterns. Based on our proposed method, we can set the scanning step size 3 times larger to perform the scanning technique of non-invasive imaging without deteriorating the retrieving quality, thus reducing the scanning time by \(8/9\).

V. CONCLUSION

In this paper, we have proposed a method based on sparse representation to perform the scanning technique of non-invasive imaging. In the scanning process, first we obtain the integrated intensity pattern with a larger scanning step size than needed. Then using sparse representation, the necessary integrated intensity pattern to make the scanning technique work well can be reconstructed and the fluorescent object can be retrieved with high quality. In general, our method can greatly accelerate the scanning process.

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