(54) Title: SYSTEM AND METHOD FOR RAPID OCT IMAGE ACQUISITION USING COMPRESSIVE SAMPLING

(57) Abstract:
A method for rapid OCT image acquisition is disclosed. The method includes acquiring by a time-domain OCT a plurality of compressive measurements \(y\) representing a set of under-sampled OCT data in a Dirac domain below a Nyquist rate by sampling...
(57) **Abrégé(suite)/Abstract(continued):**
an object of interest at randomly spaced vertical and horizontal lines in a Cartesian geometry using a raster scan, and recovering a 3D volumetric time-domain OCT image (f) from the compressive measurements (y) using compressive sampling. In a preferred embodiment, the method includes recovering the 3D volumetric time-domain OCT image (f) from the compressive measurements (y) based at least in part on a sparsifying matrix (S) capable of transforming the 3D volumetric time-domain OCT image (f) into a sparse representation, such as a matrix representation of the 3D volumetric time-domain OCT image (f) in a shift-invariant wavelet transform domain.
ABSTRACT

A method for rapid OCT image acquisition is disclosed. The method includes acquiring by a time-domain OCT a plurality of compressive measurements \( y \) representing a set of under-sampled OCT data in a Dirac domain below a Nyquist rate by sampling an object of interest at randomly spaced vertical and horizontal lines in a Cartesian geometry using a raster scan, and recovering a 3D volumetric time-domain OCT image \( f \) from the compressive measurements \( y \) using compressive sampling. In a preferred embodiment, the method includes recovering the 3D volumetric time-domain OCT image \( f \) from the compressive measurements \( y \) based at least in part on a sparsifying matrix \( S \) capable of transforming the 3D volumetric time-domain OCT image \( f \) into a sparse representation, such as a matrix representation of the 3D volumetric time-domain OCT image \( f \) in a shift-invariant wavelet transform domain.
SYSTEM AND METHOD FOR RAPID OCT IMAGE ACQUISITION USING
COMPRESSIVE SAMPLING

1. TECHNICAL FIELD

The present invention relates generally to the field of signal acquisition and
reconstruction, and more particularly, to the field of signal reconstruction of images
acquired using Optical Coherence Tomography ("OCT").

2. BACKGROUND OF THE INVENTION

Optical Coherence Tomography (hereinafter referred to as "OCT") is emerging as a
dominant medical imaging modality for diagnostic ophthalmology. Optical coherence
tomography works similarly to ultrasound tomography, however substituting use of light
waves instead of sound waves to reconstruct images of tissue layers based on the reflection
of light from tissue interfaces. By using the time-delay information contained in the light
waves which have been reflected from different depths inside a tissue sample, an OCT
system can reconstruct a depth-profile of the sample structure. Three-dimensional images
can then be created by scanning the light beam laterally across the sample surface to create
a 3D tomographic grid. Conventional OCT scanning schemes suffer from a number of
drawbacks. Morphometric analysis and clinical applications typically demand high
resolution OCT images, which necessitate dense sampling, leading to long scan times.
During such long scan times, a person subject to the OCT scan is often required to remain
still, sometimes for up to ten seconds, with a fixed gaze on a point without blinking – a
challenging feat even for the most determined and those without eye health issues. Long
scan times may inevitably increase the likelihood of image corruption from motion
artifacts, such as image blurring and ghosting resulting from the subject’s eye blinking
during an OCT scan session. Long OCT scan sessions may also cause subject discomfort
and aggravate soreness to those with eye problems who are more likely to need OCT scans.
An outstanding need therefore exists for an improved system and method for OCT image
acquisition for the benefits of reduced scan times, without significantly comprising the quality of the image acquired from the subject of interest.

Compressive sampling, or compressive sensing, is a technique for signal acquisition and reconstruction utilizing the prior knowledge that the sampled signal is sparse or compressible in nature. Conventional acquisition and reconstruction of images from frequency data using compressive sampling techniques typically follows the basic principle of the Nyquist density sampling theory, which states that to reconstruct an image, the number of Fourier samples that need to be acquired must match the desired resolution, and by extension, the number of pixels of the image. Compressive sampling suggests the possibility of new data acquisition protocols that show that super-resolved signals and images may be reconstructed from far fewer data or measurements than that which was considered necessary under the Nyquist sampling theory. An overview of compressive sampling may be found, for example, in E.J. Candes, J. Romberg, and T. Tao, Robust Uncertainty Principles: Exact Signal Reconstruction from Highly Incomplete Frequency Information, IEEE Trans. Inform. Theory, 52, 489–509 (2004); and E.J. Candes and D. L. Donoho, New Tight Frames of Curvelets and Optimal Representations of Objects with Piecewise-C2 Singularities, Communications on Pure and Applied Mathematics, 57, no. 2, 219–266 (2004).

3. SUMMARY OF THE INVENTION

Certain features, aspects and examples disclosed herein are directed to a method for rapid OCT image acquisition. Additional features, aspects and examples are discussed in more detail herein.

In accordance with a first embodiment of the invention, a method for rapid OCT image acquisition is disclosed. The exemplary method for rapid OCT image acquisition includes acquiring by a time-domain OCT a plurality of compressive measurements (y) representing a set of under-sampled OCT data in a Dirac domain below a Nyquist rate by sampling an object of interest at randomly spaced vertical and horizontal lines in a
Cartesian geometry using a raster scan, and recovering a 3D volumetric time-domain OCT image \( f \) from the compressive measurements \( y \) using compressive sampling.

Exemplary embodiments of the method of the present invention may include one or more of the following features. In some embodiments, the method for rapid OCT image acquisition further includes forming a sparsifying matrix \( S \) capable of transforming the 3D volumetric time-domain OCT image \( f \) into a sparse representation, and recovering the 3D volumetric time-domain OCT image \( f \) from the compressive measurements \( y \) based at least in part on the sparsifying matrix \( S \). According to certain embodiments, the sparsifying matrix \( S \) represents a matrix representation of the 3D volumetric time-domain OCT image \( f \) in a shift-invariant wavelet transform domain.

In some embodiments, the compressive measurements \( y \) represent a range between 25 and 77 percent of the data present in the 3D volumetric time-domain OCT image \( f \). In other embodiments, the compressive measurements \( y \) represent less than 50 percent of the data present in the 3D volumetric time-domain OCT image \( f \).

Further advantages of the invention will become apparent when considering the drawings in conjunction with the detailed description.

4. BRIEF DESCRIPTION OF THE DRAWINGS

The present invention will now be described with reference to the accompanying drawing figures, in which:

FIG. 1 illustrates schematic of a conventional time-domain OCT scan pattern,

FIG. 2 illustrates schematic of an OCT scan pattern according to an embodiment of the present method for rapid OCT image acquisition using compressive sampling.

FIG. 3 illustrates a flow diagram of a method for rapid OCT image acquisition using compressive sampling according to exemplary embodiment of the invention.

FIG. 4A illustrates an exemplary transversal slice, or C-scan, extracted from a full OCT volume of an optic nerve head acquired using conventional OCT raster scan geometry.

FIG. 4B illustrates a C-scan of a mask that discards 53% of the original samples as shown in FIG. 4A according to an embodiment of the invention.
FIG. 4C illustrates C-scan of a reconstructed OCT volume recovered from 53% of the original samples as shown in FIG. 4A missing according to an embodiment of the invention.

FIG. 4D shows contrast-enhanced differences between the results of FIG. 4A and FIG. 4C.

FIGs. 5A-5D show two vertical and horizontal original B-scans acquired by conventional OCT raster-scan geometry.

FIGs. 6B-6D show the same slices as FIG.s 5A-5D taken from a volume with 53% missing data according to an embodiment of the invention.

FIGs. 7A-7D show the same slices as FIG.s 5A-5D recovered from the compressive measurements by the CS interpolation method according to an embodiment of the invention.

FIGs. 8A-8D show the same slices as FIG.s 5A-5D recovered by a conventional bilinear interpolation of the same B-scans.

FIGs. 9A-9D show representative typical B-scans recovered according to an embodiment of the invention utilizing compressive sampling in volumes with 23, 35, 61 and 75 percent missing data.

FIG. 10A shows an extracted ILM surface from a segmentation of the original 3D image volume acquired using a conventional OCT raster scan geometry.

FIG. 10B shows an extracted ILM surface from a segmentation of a recovered 3D image volume with 53% missing data according to an embodiment of the invention.

FIG. 10C shows the average ILM where the colormap represents the variance in position in the three manual segmentations of the original image volume.

FIGs. 11A-11E show topographical Change Analysis (TCA) maps showing position of ILM surface overlaid on top of summed-voxels-projection images of recovered volumes at 23%, 35%, 53%, 61% and 75% missing data, respectively, according to an embodiment of the invention.

FIG. 12 is a graph plotting the reduction in raster scan time as a function of percent of missing data representing the extent of OCT data under-sampling according to an embodiment of the invention.
Similar reference numerals refer to corresponding parts throughout the several views of the drawings.

5. DETAILED DESCRIPTION OF THE INVENTION

To address certain shortcomings of the aforementioned prior art OCT scanning methods, in one embodiment the present invention provides a method for rapid OCT image acquisition using compressive sampling, in which OCT acquisition of a reduced random or pseudo-random subset of the raster scans that make up the 3D volumetric field of view of the entire image of a subject of interest is performed during the scanning process. Thereafter, by exploiting the sparsity of image coefficients in a predetermined transform domain (e.g. a shift-invariant wavelet transform domain), the recovery of missing samples may desirably be achieved with high fidelity, thereby reducing the overall OCT scan time and the associated patient discomfort and motion artifacts that may typically follow slower conventional OCT scanning schemes, while recovering a full 3D image of the scanned volume.

Compressive Sampling

To clarify the advantages and benefits of the present method for rapid OCT image acquisition using compressive sampling as disclosed according to embodiments of the invention herein, a discussion of compressive sampling is provided.

Prior to the introduction of compressive sampling, conventional wisdom as exemplified by the Nyquist sampling theorem states that a signal needs to be sampled at a rate greater than the inverse of twice its bandwidth to permit perfect signal reconstruction, commonly referred to as the Nyquist sampling rate. If the signal is a vector of length N, then the acquisition of at least N number of samples is required to reconstruct that signal according to Nyquist sampling methods. The sensing or measurement matrix is therefore a N*N square matrix.

Compressive sampling however permits accurate signal reconstruction from highly under-sampled measurements, i.e. data sampled at significantly below the Nyquist rate. In particular, it has been shown that when the unknown signal has an S-sparse representation,
i.e. one can find a basis in which its representation has less than S non-zero entries, compressive sampling may desirably offer successful recovery with relatively few under-sampled measurements K, where K<<N. Accordingly, a sample measurement matrix may therefore be reduced to a K*N matrix. To allow for successful signal reconstruction, the theory of compressive sampling provides that the measurement matrix needs to be incoherent or uncorrelated with the sparsifying matrix used to transform the signal into its sparse representation, or satisfies the so-called Restricted Isometry Property (RIP). To satisfy the mutual incoherence criterion, random measurement matrices are often used since they will most likely be uncorrelated with any specific sparsifying matrix. See E.J. Candes, J. Romberg, and T. Tao, Robust uncertainty principles: Exact recovery from highly incomplete Fourier information, IEEE Trans. Inform. Theory, 52 489-509 (2004). Then, relying on the fact that the underlying signal is compressible, an appropriate non-linear method enforcing signal sparsity and consistency of the reconstruction with the acquired samples can be used to reconstruct the signal from randomly under-sampled data.

Accordingly, a successful application of compressive sampling can be said to have three requirements: 1) Transform sparsity – the desired image should have a sparse representation in a known transform domain (i.e. it must be compressible by transform coding); 2) Incoherence of under-sampling artifacts – the artifacts in linear reconstruction caused by K-sparse under-sampling should be incoherent in the sparsifying domain; and 3) Nonlinear reconstruction – the image should be reconstructed by a non-linear method which simultaneously enforces sparsity of the image representation and consistency of the reconstruction with the acquired samples.

**Transform Sparsity**

As suggested by the theory of compressive sampling, successful signal recovery from under-sampled data depends in part on the signal having a sparse representation in a known transform domain. Hereinafter, a transform that provides sparse representation of 3D OCT image data in a basis different from one in which the image data is acquired is referred to as a “sparsifying transform”, a mathematical operator that maps a vector of image data to a sparse vector. In a preferred embodiment of the invention, a suitable
sparsifying transform for the method for rapid OCT image acquisition using compressive sampling to recover data may be chosen depending on several factors:

1. Sparsity. The sparsifying transform may desirably be able to capture most of the energy of the sampled OCT signal with only a few coefficients.

2. Incoherence. The basis functions of the sparsifying transform may desirably be as incoherent as possible with respect to the domain from which compressive signal measurements are acquired.

3. Tight frame. The sparsifying transform may desirably form a tight frame, or obey a generalized Parseval's identity.

4. The sparsifying transform may desirably pass the dot-test.

Suitable sparsifying transforms satisfying the above-mentioned four factors according to an embodiment of the invention may include the curvlet transform, surfacelet transform, and wavelet transform, for example. In a preferred embodiment of the method for rapid OCT image acquisition using compressive sampling, the sparsifying transform may be a shift-invariant wavelet transform.

In one embodiment of the method for rapid OCT image acquisition using compressive sampling, the problem of single recovery of a 3D volumetric OCT image from a subset of under-sampled OCT data may be characterized by the following forward model:

\[ y = RMf + n \quad (1.1) \]

In the equation (1.1), \( f \) is a vector of \( N \) entries that denotes the 3D image of a subject of interest, such as a biological tissue structure for example, defined on a 3D Cartesian grid, obtainable by OCT using conventional raster scan geometry. In one embodiment of the invention, the method for rapid OCT image acquisition using compressive sampling proposes to recover the full 3D image \( f \) by taking \( K \) measurements of the full 3D image \( f \) at a sampling rate significantly below the Nyquist rate. The reduced
number of measurements from which the full data vector \( \mathbf{f} \) may be recovered are hereinafter referred to as compressive measurements or samples, represented by vector \( \mathbf{y} \) in the equation (1.1) with \( K \) entries, where \( K \ll N \), and where each component of \( \mathbf{y} \) is a linear measurement of the full data vector \( \mathbf{f} \). Symbol \( n \) represents the noise present in the acquired OCT data. In one embodiment of the present invention, the \( K \) compressive measurements represented by \( \mathbf{y} \) may comprise a subset of measurements containing between 25% and 77% of the number of measurements or samples in the full 3D image \( \mathbf{f} \), for example.

The matrix \( \mathbf{M} \) in equation (1.1) refers to the domain from which the compressive measurements \( \mathbf{y} \) are acquired. In a preferred embodiment of the invention, the OCT is a time-domain OCT, and OCT images are acquired in a 3D space with Cartesian geometry. As such, in the signal recovery problem as represented by the equation (1.1), \( \mathbf{M} \) is the identity or the Dirac measurement basis such that \( \mathbf{M} := \mathbf{I}_d \), where identity matrix \( \mathbf{I}_d \) has a dimension of \( d \times d \). The matrix \( \mathbf{R} \) is a restriction operator, i.e., it extracts those rows from the identity matrix \( \mathbf{M} \) that represent the number of compressive measurements that are actually acquired. The dimensions of the measurement basis and the restriction operator may be determined by the acquisition geometry, or the raster scanning geometry of the OCT image acquisition system or scanning path.

As suggested by the theory of compressive sampling, the basis functions of the sparsifying transform selected in embodiments of the invention may desirably be as incoherent as possible with respect to the domain from which compressive measurements are acquired, and thereby represent mutual incoherency. It has been shown that sampling an object of interest in a measurement basis at randomly spaced vertical and horizontal lines in a Cartesian geometry skipping a large portion of the image during acquisition satisfies this mutual incoherency criterion, as random measurement matrices are often used since they will most likely be uncorrelated with any specific sparsifying matrix. See E.J. Candes, J. Romberg, and T. Tao, *Robust uncertainty principles: Exact recovery from highly incomplete Fourier information*, IEEE Trans. Inform. Theory, 52 489-509 (2004). In one embodiment of the present invention, the acquired subset of OCT image data or measurements, \( \mathbf{y} \), may be acquired corresponding to random vertical and horizontal lines.
imposed on the physical volume to be imaged. Such random vertical and horizontal
scanning or measurement lines may be generated by a binary restriction mask $R$ comprising
vertical and horizontal lines with uniform and random placement, which may be applied
during data acquisition such that certain random horizontal and vertical raster-scan lines are
skipped during the raster-scanning process, thereby generating randomly sub-sampled OCT
image volumes $y$ of the 3D image of a subject of interest $f$. As such, the application of a
restriction mask $R$ results in the reduction in the number of samples being acquired as
compared to a conventional time-domain OCT raster scan, as best illustrated by FIGs. 1 and
2.

As shown in FIG. 1, which illustrates a schematic of a conventional time-domain OCT
scan pattern, the volume of a subject of interest 110, which may comprise a biological body
or tissue structure such as an human eye, is imaged by OCT using a typical raster scan
geometry whereby every point in the volume is imaged by scanning every horizontal line
130 in the volume with a light beam 120. Put simply, 100% of the volume of the subject of
interest 110 is scanned or imaged. In an embodiment of the present method for rapid OCT
image acquisition using compressive sampling only random, fixed lines in the image
volume are scanned or imaged to form compressively sampled OCT image data $y$. FIG. 2
illustrates a schematic of an OCT scan pattern according to an embodiment of the present
method for rapid OCT image acquisition using compressive sampling. As shown in FIG. 2,
a volume of a subject of interest 210 is imaged by scanning only selected, randomly-spaced
fixed horizontal lines 230 and vertical lines 240, whereby only a subset of the raster scans
that make up the 3D volumetric field of view of the entire image of a subject of interest is
sampled. In one embodiment, compressive measurements represent 25% of the total raster
scans that make up the 3D volumetric field of view of the entire image with 75% of the data
missing. In other embodiments, compressive measurements represent subsets of 77%,
65%, 47% and 39% of the total raster scans of the entire image sampled, with 23%, 35%,
53%, and 61% of the data missing, respectively. Still in some embodiments, the
compressive measurements ($y$) represent a range between 25 and 77 percent of the data
present in the 3D volumetric time-domain OCT image ($f$). In other embodiments, the
compressive measurements \( y \) represent less than 50 percent of the data present in the 3D volumetric time-domain OCT image \( f \).

Referring again to the signal recovery problem in equation (1.1), ignoring temporarily the noise \( n \), a solution to the signal recovery problem is to solve a matrix equation of the form \( y = R M f \). Since vector \( y \) is of length \( K \) and vector \( f \) is of length \( N \) with \( K << N \), this system of linear equations is underdetermined and does not have a unique solution in general. However, the theory of compressive sampling states that adding the constraint that the signal \( f \) is compressible enables one to solve this underdetermined system of linear equations. That is, if one can find a sparsifying transform domain represented by matrix \( S \) that offers good compressibility, i.e. a small number of coefficients \( x = S f \) can describe the 3D image \( f \) in the sparsifying domain, then the signal \( f \) can be represented as \( f = S^H x \), where \( S^H \), the conjugate transpose of matrix \( S \), is the synthesis operator transforming the coefficients \( x \) from the sparsifying domain back to the image domain represented by matrix \( M \), or the domain from which compressive measurements are acquired and in which the signal is wished to be reconstructed. Therefore, given incomplete measurements \( y \) of the image \( f \), instead of recovering the unknown image \( f \) directly, in an embodiment of the present invention, the unknown sparse coefficients \( x \) parameterizing \( f \) may be selected such that the reconstructed signal \( S^H x \) followed by the application of a known restriction mask \( R \) is close to the observed under-sampled data \( y \), subject to the constraint that the \( L_2 \) mean-squared error \( \| y - R S^H x \|_2 \) is small. Put in other words, given a set of incomplete measurements \( y \) of the signal \( f \), an approximation \( \tilde{f} \) such is desired to be obtained such that (i) \( \tilde{f} = S^H x^\ast \), where \( x^\ast \) is sparse, and (ii) \( \| y - R S^H x \|_2 \) is small. From the many potential solutions to this problem, the desired \( x^\ast \) is one with the smallest \( L_1 \) norm \( \| x^\ast \|_1 \), representing a measure of sparsity. Therefore, the recovery of sparsely sampled OCT images may be realized by solving the following optimization problem via \( L_1 \) minimization:

\[
x^\ast = \arg \min x^\ast \| x^\ast \|_1 \text{ subject to } \| y - R S^H x \|_2 \leq \epsilon \quad (1.2)
\]

In a preferred embodiment of the present invention, the matrix \( S^H \) may be determined as a synthesis matrix in the shift-invariant wavelet domain which offers good
compressibility of OCT images. Other sparsifying domains that offer good compressibility of OCT images and satisfy the conditions as discussed in the above-section titled "Transform Sparsity" may also be used in other embodiments of the invention.

The optimization problem in equation (1.2) is a convex optimization problem and may be cast into a linear program to solve the problem in equation (1.2), from which suitable conventional linear programs from the field of convex optimization may be employed. In a preferred embodiment of the present invention, the method for rapid OCT image acquisition using compressive sampling may employ the iterative soft thresholding (IST) solver to solve the $\ell_1$ minimization problem given in equation (1.2). Before the IST solver may be applied directly to solve the $\ell_1$ minimization problem, equation (1.2) is reformulated into a series of unconstrained problems using Lagrange multipliers $\lambda$ as:

$$ x^* = \arg\min_{x} \left\{ \|x\|_1 + \lambda \|y - RX^Hx\|_2 \right\} \quad (1.3) $$

where $\lambda$ is a parameter that controls the tradeoff between the sparsity of the solution (minimization of $\ell_1$ norm) and the $\ell_2$ data misfit. To simplify notation, a matrix $A$ is defined to be $A: \text{RMS}^H$.

An exemplary IST program code according to an embodiment of the invention for solving the $\ell_1$ minimization problem may be represented as follows:

**Result:** Estimate for $x$

1 initialization;

2 $x_0 \leftarrow$ initial guess for $x$;

3 $\lambda_0 \leftarrow$ initial Lagrange multiplier;

4 $L \leftarrow$ number of inner iterations;

5 while $\|y - Ax\|_2 \geq c$ do

6 for $\ell = 1$ to $L$ do

7 $i \leftarrow i + 1$;

8 $x_{i+1} \leftarrow S_{\lambda}(x_i + A^H(y - Ax_i))$;

9 end

10 $\lambda_{k+1} \leftarrow a_k \lambda_k$ with $0 < a_k < 1$;

11 $k \leftarrow k + 1$;
12 end

Using the IST solver such as the above-described exemplary IST solution method, the iterative update \( x \rightarrow T_\lambda (x + A^T(y - Ay)) \) desirably converges to the solution for a particular value of \( \lambda \) as the number of iterations goes to infinity. In practice, only a finite number of iterations may be required to achieve convergence of \( x^- \). According to an embodiment of the invention, after obtaining an approximation of the sparsifying coefficients \( x^- \), the full OCT image \( f \) is recovered by the following equation:

\[
f^* = S^H x^- (1.4)
\]

In a preferred embodiment, the full 3D OCT image volume may be recovered with the IST solver using approximately six (6) inner loops and forty (40) outer loop iterations, for example.

In the embodiments of the present inventive method for rapid OCT image acquisition using compressive sampling as above described thus far, the OCT system is a time-domain OCT system and the measurement basis in which the compressive measurements are acquired is the Dirac basis, however in other embodiments of the invention, other measurement bases may be utilized by way of modifying the OCT system hardware by which the OCT data is acquired, as may be obvious to a person skilled in the OCT art. For example, in spectral-domain OCT systems, the measurement basis used in an embodiment of the present inventive method may be the Fourier basis. One way of checking whether a specific measurement matrix will allow for sparse solutions to be recovered and thereby be potentially suitable for utilization according to an embodiment of the present invention, is to check if the measurement matrix follows the Restricted Isometry Property (RIP).

In a preferred embodiment of the invention, the IST solver is selected as the \( \ell^1 \) minimization algorithm for its fast convergence and ease of implementation. However, in other embodiments, any other suitable known \( \ell^1 \) minimization algorithms may be applied, such as iteratively reweighted least squares, SPGL1 solver, projected gradient methods, and iterative hard-thresholding, for example.

FIG. 3 illustrates a flow diagram of a method for rapid OCT image acquisition using compressive sampling according to exemplary embodiment of the invention. As shown at
operation 310, the method begins with the modeling of the signal recovery problem as shown in equation (1.1) in the physical domain, or time-domain OCT.

Following the modeling of the signal recovery problem, at step 320, K compressive measurements \( (y) \) representing a subset of the raster scans that make up the 3D volumetric field of view of the entire image \( (f) \) of a subject of interest are sampled in the Dirac domain by random under-sampling.

Following data acquisition at operations 310 and 320, the method for rapid OCT image acquisition using compressive sampling proceeds to signal reconstruction. At operation 330, a sparsifying domain that offers good compressibility of the full 3D image \( f \) is selected. In the embodiment as shown in FIG. 3, the sparsifying transform used is the shift-invariant wavelet transform. Next, the recovery of sparsely sampled OCT images modeled by the problem in equation (1.1) may be realized by solving the optimization problem via \( \ell_1 \) minimization in equation (1.2) using a suitable \( \ell_1 \) minimization algorithm, such as using the IST solver to find an approximation of the sparsifying coefficients \( x^* \) at step 340. Finally, the full 3D image \( f \) is reconstructed using equation (1.4) in the physical domain, or Dirac basis at step 350.

Accordingly, as described by illustrative embodiments, the method for rapid OCT image acquisition using compressive sampling of the invention, by acquiring a small random or pseudo-random subset of the raster scans that make up the 3D volumetric field of view of the entire OCT image of a subject of interest, followed by exploiting the sparsity of image coefficients in a predetermined transform domain (e.g. shift-invariant wavelet transform domain), enables the recovery of missing samples with high fidelity, thereby advantageously reducing the overall OCT scan time and the associated patient discomfort and motion artifacts that typically follow conventional OCT scanning schemes.

**Examples**

A full 3D OCT original image volume \( (f) \) was acquired by raster-scanning the optic nerve head of a healthy male subject using OCT. An example of a transversal slice, or C-scan, extracted from the OCT volume is shown in FIG. 4A. To simulate the sparsely sampled OCT image volume \( (y) \) that would be acquired by a method of randomly skipping
horizontal and vertical raster-scan lines to rapidly sub-sample the desired volume, a binary restriction mask \( R \) is applied to this full OCT image \( f \). This mask \( R \) consists of vertical and horizontal lines with random (but fixed) placing. Five levels of restriction mask removing 23, 35, 53, 61, and 75 percent of sampled OCT data and corresponding to sub-sampling rates of 77, 65, 47, 39 and 25 percent, respectively, were created, and were applied to the original image volume to generate five different sub-sampled volumes \( y \). An example of mask \( R \) that discards 53% of the original samples to represent a 47% sub-sampling rate is shown in FIG. 4B where the red lines denote data that was discarded. The four green lines represent recovered B-scans shown in FIGs. 5A-5D.

The full 3D OCT image volume for each level of subsampling was recovered according to an embodiment of the present method for rapid OCT image acquisition using compressive sampling employing an exemplary IST solver (detail: using 6 inner and 40 outer loop iterations). SNR based on recovered images corresponding to 23, 35, 53, 61, and 75 percent missing data was found to be 14.9, 13.0, 10.6, 9.8, and 7.5 db respectively showing decreasing SNR with increasing degradation due to missing data. The compressive sampling ('CS') recovery result for 53% missing data (corresponding to a 47% sub-sampling rate) and the error \( |f - f'| \) image for this cross-section is shown in FIGs. 4C and 4D, respectively.

FIGs. 5A-5D show two vertical (FIGs. 5A and 5B) and horizontal (FIGs. 5C and 5D) original B-scans acquired from conventional OCT using raster-scan geometry. FIGs. 6A-6D show the same slices as FIG.s 5A-5D, respectively, taken from an image volume with 53% missing data, corresponding to an imaging sampling rate of 47% of the total volume desired to be imaged. FIGs. 7A-7D show the same slices as FIG.s 5A-5D, respectively, after recovery from the compressed or sparsely sampled scan slices shown in FIGs. 6A-6D using the CS interpolation method as detailed above according to an embodiment of the invention. FIGs. 8A-8D show the same slices as FIG.s 5A-5D, respectively, recovered by bilinear interpolation of the same B-scans of FIGs. 5A-5D.

Comparing the two vertical and horizontal B-scans recovered from a volume with 53% missing data (corresponding to a compressive sampling rate of 47%) using the CS interpolation method as are shown in FIGs. 7A-7D with bilinear interpolation of the same
B-scans as shown in FIGS. 8A-8D, one can observe a distinct, undesirable "staircase" pattern or artifact in the bilinear interpolation results which are desirably absent in the CS-based image recovery.

FIGs. 9A-9D show representative typical B-scans recovered using the CS interpolation in imaged volumes with 23, 35, 61 and 75 percent missing data, respectively (corresponding to compressive sampling rates of 77, 65, 29 and 25 percent, respectively), from a region where data was not sampled. It can be seen that the overall image quality begins to deteriorate progressively from FIGs. 9A to 9D as more data is discarded (corresponding to less data acquired in a compressed sampling acquisition scan), but nevertheless, the fidelity is still acceptable even for an image volume recovered from a scan with 25% sampling (or 75% missing data as compared to a full scan) as shown in FIG. 9D.

Validation

Experiments were performed to quantify how the degradation in recovered images affected the measurement of anatomically meaningful parameters such as the optic nerve cup shape from ophthalmologic OCT image volumes acquired using compressive sampling scanning and recovery methods such as disclosed above according to embodiments of the present invention. This was done by manually segmenting, using established protocols, the clinically relevant Inner Limiting Membrane ("ILM") surface for the reconstructed image volume for each of five exemplary levels of image degradation. These segmentations were performed on each B-scan slice of every volume.

The extracted ILM surface from one of the segmentations of the original 3D image is shown in FIG. 10A, where the color map represents the vertical height (to better present the 3D nature of the cup). The ILM surface extracted from the recovered volume with 53% missing data (corresponding to a sampling rate of 47%), shown in FIG. 10B, closely resembles that of the original ILM shown in FIG. 10A.

The recovered image may be deemed to have passed a test of required fidelity for potential morphometric use if the location of the ILM surface segmented from the recovered image falls within the variability of the surface segmentations performed multiple times on the original image volume by the same rater. To quantify the
segmentation variability due to the manual rater, the ILM in the original 3D image was segmented thrice, each time by the same rater but without consulting the previous segmentations.

Using these segmented surface images, an average ILM surface was created representing a baseline or ground truth of the ILM surface. The standard deviation of each point's position as observed in the three manual segmentations of the ILM surface was calculated, and the height or color of the colormap shown in FIG. 10C represents the variance in position in the three manual segmentations of the original image volume. The surface shown in FIG. 10C is therefore the average ILM where the colormap represents the variance in position in the three manual segmentations of the original image volume.

For each point on the ILM surface segmented from the reconstructed data, the relative position to the average ILM surface (the baseline) was found. This process was used to generate so-called Topographical Change Analysis (TCA) maps representing the variability in position of the ILM surface from a known baseline/ground truth.

Topographical Change Analysis (TCA) maps showing position of ILM surface overlaid on top of summed-voxels-projection images of recovered volumes at 23%, 35%, 53%, 61% and 75% missing data (corresponding to sampling rates of 77%, 65%, 47%, 39%, and 25% respectively in embodiments of the present invention) are shown in FIGs. 11A-11E, respectively. The relative surface position relative to standard deviation is shown in FIGs. 11A-11E with red representing posterior surface location, and green representing anterior surface location in the recovered image.

It can be seen that in the illustrative experimental embodiments discussed above, the quality of the summed voxel projection images begins to deteriorate at the 61% missing data volume shown in FIG. 11D (corresponding to a sampling rate of 39%), but is still acceptable even at 75% missing data shown in FIG. 11E (corresponding to a sampling rate of 25%). For the volume that was recovered from 23% missing data shown in FIG. 11A, nowhere did the segmentations fall outside the one standard deviation regions. For the other cases with more missing data as shown in FIGs. 11B-11E, most points in the image were reconstructed faithfully so that the errors in position exceeded one standard deviation in only a few locations. These were typically in slices with missing data that were located
along the steeply sloping part of the ILM surface. Given that only a few locations in recovered surfaces deviated by more than one standard deviation for each of the five cases tested (as an example, <8% points on the recovered ILM surface were farther than one standard deviation in the case of 75% missing data), clinical measurements such as cup volume and area desirably did not significantly differ from the measurements made on the original volume, as shown below in Table 1.

<table>
<thead>
<tr>
<th>% Missing Data</th>
<th>23</th>
<th>35</th>
<th>53</th>
<th>61</th>
<th>75</th>
</tr>
</thead>
<tbody>
<tr>
<td>DS.A. (%)</td>
<td>0.49</td>
<td>0.65</td>
<td>4.79</td>
<td>4.25</td>
<td>6.51</td>
</tr>
<tr>
<td>DVL. (%)</td>
<td>0.36</td>
<td>0.81</td>
<td>1.14</td>
<td>0.85</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 1

Changes in surface area and volume of the nerve cup resulting from the use of images recovered from compressively sampled scans according to an embodiment of the invention were assessed to be clinically negligible.

The reduction in scan time, presented as a function of percent of missing data, is shown in FIG. 12. The benefits in reduced scan time of the proposed randomly compressed scanning patterns according to embodiments of the present invention begin to be observable when one discards approximately 25% of the data, or more (corresponding to a sampling rate of 75% or lower). Using a compressive subsampling pattern with sampling rates of 47% or 39% (corresponding to 53% or 61% missing data) roughly halved the acquisition time.

The exemplary embodiments herein described are not intended to be exhaustive or to limit the scope of the invention to the precise forms disclosed. They are chosen and described to explain the principles of the invention and its application and practical use to allow others skilled in the art to comprehend its teachings.

As will be apparent to those skilled in the art in light of the foregoing disclosure, many alterations and modifications are possible in the practice of this invention without departing from the spirit or scope thereof. Accordingly, the scope of the invention is to be construed in accordance with the substance defined by the following claims.
WHAT IS CLAIMED IS:

1. A method for rapid Optical Coherence Tomography image acquisition of a biological tissue comprising:
   acquiring by a time-domain Optical Coherence Tomography a plurality of compressive measurements (y) from an Optical Coherence Tomography scanner representing a set of under-sampled Optical Coherence Tomography data in a Dirac domain below a Nyquist rate by sampling the biological tissue at randomly spaced vertical and horizontal lines in a Cartesian geometry using a raster scan; and
   recovering a 3D volumetric time-domain Optical Coherence Tomography image (f) of the biological tissue from the compressive measurements (y) using compressive sampling.

2. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to claim 1 wherein the biological tissue is human tissue.

3. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to claim 1 wherein the human tissue is human eye tissue.

4. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to any one of claim 1, 2 or 3, further comprising:
   forming a sparsifying matrix (S) capable of transforming the 3D volumetric time-domain Optical Coherence Tomography image (f) into a sparse representation; and
   recovering the 3D volumetric time-domain Optical Coherence Tomography image (f) from the compressive measurements (y) based at least in part on the sparsifying matrix (S).

5. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to claim 4, wherein the sparsifying matrix (S) represents a
matrix representation of the 3D volumetric time-domain Optical Coherence Tomography image (f) in a shift-invariant wavelet transform domain.

6. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to any one of claims 1 to 5, wherein the compressive measurements (y) represent a range between about 25 and about 77 percent of the data present in the 3D volumetric time-domain Optical Coherence Tomography image (f).

7. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to any one of claims 1 to 5, wherein the compressive measurements (y) represent less than about 50 percent of the data present in the 3D volumetric time-domain Optical Coherence Tomography image (f).

8. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to any one of claims 1 to 5, wherein the compressive measurements (y) represent about 25 percent of the data present in the 3D time-domain Optical Coherence Tomography image (f).

9. The method for rapid Optical Coherence Tomography image acquisition of a biological tissue according to claim 4, wherein the sparsifying matrix (S) represents a matrix representation of the 3D volumetric time-domain Optical Coherence Tomography image (f) in at least one of: a curvlet transform, surfacelet transform, and wavelet transform.

10. The method for rapid Optical Coherence Tomography image of a biological tissue acquisition according to any one of claims 1 to 9, wherein recovering a 3D volumetric time-domain Optical Coherence Tomography image (f) from the compressive measurements (y) using compressive sampling additionally comprises using an iterative soft thresholding solver.
11. The method for rapid Optical Coherence Tomography image of a biological tissue acquisition according to any one of claims 1 to 10, additionally comprising:
   analyzing said 3D volumetric time-domain Optical Coherence Tomography image (f) for at least one ophthalmological criterion.
Data acquisition

Model in physical domain

random under-sampling

Data in Dirac domain

Wavelet Recovery

Dirac data in Wavelet domain

\( \hat{x} = \text{arg min}_x \|x\|_1 \) s.t. \( \|y - RS^H x\|_2 \leq \epsilon \)

Recovered Wavelet coefficients

\( \hat{r} = S^H \hat{x} \)

Recovered Dirac Modes
First row: FIG. 5A, 5B; 5C, 5D
Second row: FIG. 6A, 6B; 6C, 6D
Third row: FIG. 7A, 7B; 7C, 7D
Fourth row: FIG. 8A, 8B; 8C, 8D
Data acquisition

Model in physical domain

random under-sampling

Data in Dirac domain

Wavelet Recovery

Dirac data in Wavelet domain

\[ \hat{x} = \arg \min_x \|x\|_1 \quad \text{s.t.} \quad \|y - RS^Hx\|_2 \leq \epsilon \]

Recovered Wavelet coefficients

\[ \bar{f} = S^H\hat{x} \]

Recovered Dirac Modes