OCT VOLUMETRIC DATA RESTORATION VIA PRIMAL-DUAL PLUG-AND-PLAY METHOD

S. Muramatsu[1,4], S. Choi[1,4], S. Ono[2],
T. Ota[3,4], F. Nin[3,4], H. Hibino[3,4]

[1]Faculty of Eng., Niigata Univ. [2]IIR, Tokyo Institute of Tech.
[3]School of Medicine, Niigata Univ. [4]AMED, AMED-CREST

Apr. 20, 2018

MSIPLab

Contents

MSIPLab

Background

Auditory mechanism in cochlea is unclear. ∵ Never observed *in-vivo*

- Sensory epithelium in a living animal has strong nonlinear characteristics, which cannot be seen in dead animals.
- Need understanding the mechanism for science and medicine
- Try to observe sensory epithelial vibration *in vivo*

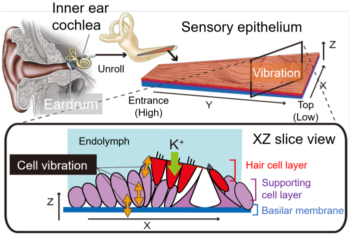


Figure: Structure of Sensory Epithelium

We develop a multifrequency-swept (MS) full-field (*en-face*) optical coherence tomography (OCT) device.

Why MS *en-face* OCT?

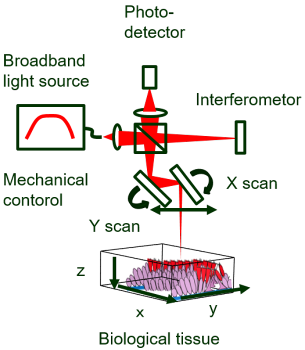


Figure: Conventional SD-OCT

Why MS *en-face* OCT?

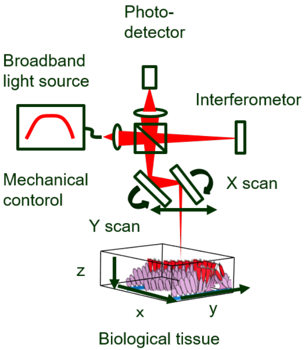


Figure: Conventional SD-OCT

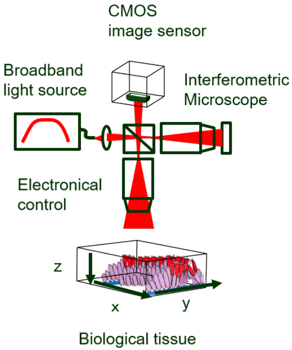


Figure: MS *en-face* OCT (Ours)

MS *en-face* OCT takes XY plane shots with Z scan.

Fast acquisition is suitable for observation of vibration.

Problem & Purpose

Problem

- Microscope expands the light spatially.
  $\longrightarrow$ Intensity becomes weak and S/N degrades.
- In addition to denoising, interference fringe should be removed.
  $\longrightarrow$ Inverse problem with band-pass type mesurement process

Our previous work adopted ISTA as denoiser [APSIPA ASC 2015].

Pros No matrix inversion is required.

Cons Denoiser is limited and hard constraint is inavailable.

Purpose

Gain the performance by updating the MODEL and ALGORITHM

Hard Constraint & Variety of Denoiser

Device Configuration

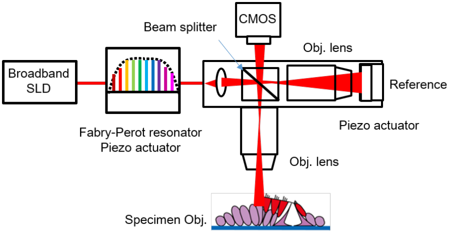


Figure: MS *en-face* OCT device

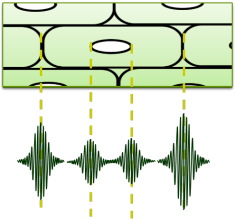


Figure: Illustration of responses

- Generate optical comb from broadband SLD light source
- Scan depth by controlling interference peak with Piezo actuator
- Separate the optical comb with a beam splitter
- Expand field of view with objective lens
- Acquire interference fringe between reflected lights

Observation Model

We approximate the interference by the following coherence function.

Cosine-modulated Gaussian function

$$p[\mathbf{m}] = \alpha\delta[m_\mathrm{x}]\delta[m_\mathrm{y}]\exp\left(-\frac{m_\mathrm{z}^2}{2\sigma_\mathrm{p}^2}\right)\cos\left(\omega_\mathrm{p} m_\mathrm{z}\right),\ \ \mathbf{m}\in\mathbb{Z}^3$$

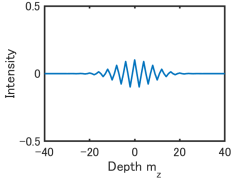


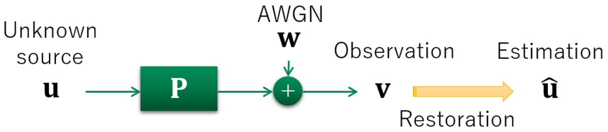
Figure: Discrete model of coherence function.

- Standard deviation: $\sigma_\mathrm{p} = 2$
- Angular Freq.: $\omega_\mathrm{p} = 0.4\pi$
- Amplitude α is set so that $\sigma_1(\mathbf{P}) = 1$.

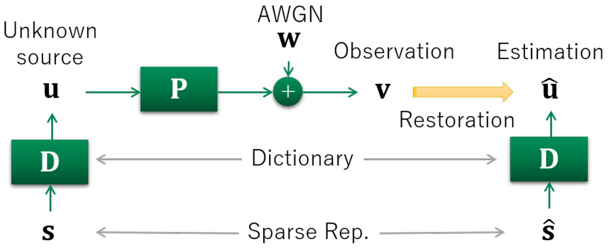
($\mathbf{P}$ is the convolution matrix, and $\sigma_1(\cdot)$ denotes the largest singular value.)

Problem Setting

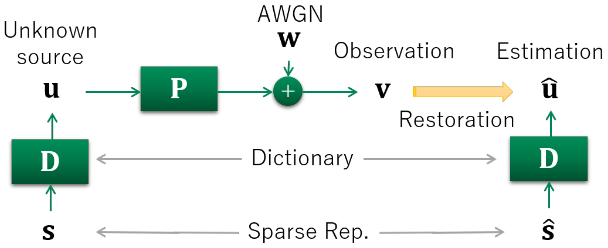
Problem Setting



Problem Setting

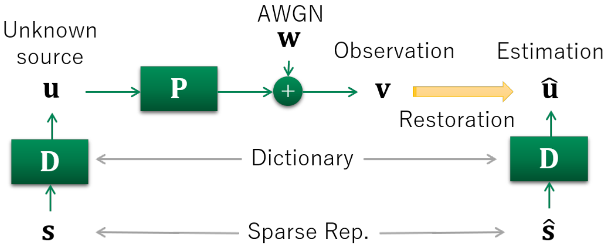


Problem Setting



Reflection **u** is bounded and is sparsely represented through Dictionary **D**.

Problem Setting

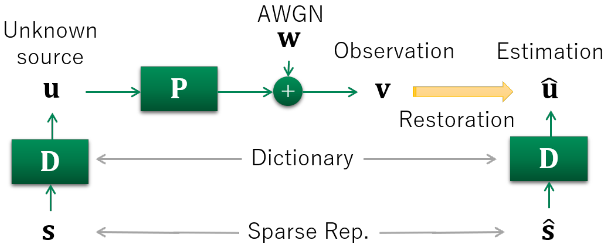


Reflection **u** is bounded and is sparsely represented through Dictionary **D**.

Assumption

$$\mathbf{v} = \mathbf{P}\mathbf{u} + \mathbf{w}$$
$$\mathbf{u} = \mathbf{D}\mathbf{s} \in [-1, 1]^N$$

Problem Setting



Reflection $\mathbf{u}$ is bounded and is sparsely represented through Dictionary $\mathbf{D}$.

Assumption

$$\mathbf{v} = \mathbf{P}\mathbf{u} + \mathbf{w}$$
$$\mathbf{u} = \mathbf{D}\mathbf{s} \in [-1, 1]^N$$

Problem Setting

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} \frac{1}{2}\|\mathbf{P}\mathbf{D}\mathbf{s} - \mathbf{v}\|_2^2 + \lambda\mathcal{R}(\mathbf{s}), \text{ s.t. } \mathbf{u} \in [-1, 1]^N$$
$$\hat{\mathbf{u}} = \mathbf{D}\hat{\mathbf{s}}$$

We propose to adopt Primal-Dual Plug-and-Play (PDPnP) method.

MSIPLab

Restoration Model

PDPnP solves the following problem [S. Ono, SPL2017]:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathbb{R}^L} \mathcal{R}(\mathbf{x}) + \mathcal{F}_{\mathbf{v}}(\mathbf{\Phi}\mathbf{x}) \text{ s.t. } \mathbf{\Psi}\mathbf{x} \in C,$$

- $\mathcal{R}(\cdot)$: Regularizer
- $\mathcal{F}_{\mathbf{v}}(\cdot)$: Data fidelity
- $\mathbf{\Phi}$: Linear measurement Proc.
- $\mathbf{\Psi}$: Linear generation Proc.
- C: Hard constraint

Restoration Model

PDPnP solves the following problem [S. Ono, SPL2017]:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathbb{R}^L} \mathcal{R}(\mathbf{x}) + \mathcal{F}_{\mathbf{v}}(\boldsymbol{\Phi}\mathbf{x}) \text{ s.t. } \boldsymbol{\Psi}\mathbf{x} \in C,$$

- $\mathcal{R}(\cdot)$: Regularizer $\longleftarrow$ Determined by pluggable Gaussian denoiser
- $\mathcal{F}_{\mathbf{v}}(\cdot)$: Data fidelity $\longleftarrow$ $\mathcal{F}_{\mathbf{v}}(\cdot) = (2\lambda)^{-1}\|\cdot - \mathbf{v}\|_2^2$ (AWGN)
- $\boldsymbol{\Phi}$: Linear measurement Proc. $\longleftarrow$ **PD** (Coherence Fcn. & Dic.)
- $\boldsymbol{\Psi}$: Linear generation Proc. $\longleftarrow$ Determined by pluggable Dic. **D**
- C: Hard constraint $\longleftarrow$ $[-1, 1]^N$ (Range of reflection)

Restoration Model

PDPnP solves the following problem [S. Ono, SPL2017]:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathbb{R}^L} \mathcal{R}(\mathbf{x}) + \mathcal{F}_{\mathbf{v}}(\boldsymbol{\Phi}\mathbf{x}) \text{ s.t. } \boldsymbol{\Psi}\mathbf{x} \in C,$$

- $\mathcal{R}(\cdot)$: Regularizer $\longleftarrow$ Determined by pluggable Gaussian denoiser
- $\mathcal{F}_{\mathbf{v}}(\cdot)$: Data fidelity $\longleftarrow$ $\mathcal{F}_{\mathbf{v}}(\cdot) = (2\lambda)^{-1}\|\cdot - \mathbf{v}\|_2^2$ (AWGN)
- $\boldsymbol{\Phi}$: Linear measurement Proc. $\longleftarrow$ **PD** (Coherence Fcn. & Dic.)
- $\boldsymbol{\Psi}$: Linear generation Proc. $\longleftarrow$ Determined by pluggable Dic. **D**
- C: Hard constraint $\longleftarrow$ $[-1,1]^N$ (Range of reflection)

Problem setting (revisited)

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}\in\mathbb{R}^L} \frac{1}{2}\|\mathbf{PDs} - \mathbf{v}\|_2^2 + \lambda\mathcal{R}(\mathbf{s}), \text{ s.t. } \mathbf{Ds} \in [-1,1]^N$$

Restoration Algorithm

Algorithm 1 Primal-Dual Plug-and-Play (PDPnP) Image Restoration

Input: $\mathbf{x}^{(0)}$, $\mathbf{y}_1^{(0)}$, $\mathbf{y}_2^{(0)}$ % $\mathbf{x} = \mathbf{s}$

Output: $\mathbf{x}^{(n)}$

1: **while** a stopping criterion is not satisfied **do**

2: $\mathbf{x}^{(n+1)} = \mathfrak{G}_{\mathcal{R}}\left(\mathbf{x}^{(n)} - \gamma_1\left(\mathbf{\Phi}^\mathsf{T}\mathbf{y}_1^{(n)} + \mathbf{\Psi}^\mathsf{T}\mathbf{y}_2^{(n)}\right), \sqrt{\gamma_1}\right)$ % Regularized GDN

3: $\mathbf{y}_1^{(n)} \leftarrow \mathbf{y}_1^{(n)} + \gamma_2\mathbf{\Phi}\left(2\mathbf{x}^{(n+1)} - \mathbf{x}^{(n)}\right)$ % $\mathbf{\Phi} = \mathbf{PD}$

4: $\mathbf{y}_2^{(n)} \leftarrow \mathbf{y}_2^{(n)} + \gamma_2\mathbf{\Psi}\left(2\mathbf{x}^{(n+1)} - \mathbf{x}^{(n)}\right)$ % Dictonary $\mathbf{\Psi} = \mathbf{D}$

5: $\mathbf{y}_1^{(n+1)} = \mathbf{y}_1^{(n)} - \gamma_2 \mathrm{prox}_{\frac{1}{\gamma_2}\mathcal{F}_\mathbf{v}}\left(\frac{1}{\gamma_2}\mathbf{y}_1^{(n)}\right)$ % $\mathcal{F}_\mathbf{v}(\cdot) = (2\lambda)^{-1}\|\cdot - \mathbf{v}\|_2^2$

6: $\mathbf{y}_2^{(n+1)} = \mathbf{y}_2^{(n)} - \gamma_2 P_C\left(\frac{1}{\gamma_2}\mathbf{y}_2^{(n)}\right)$ % $P_C(\cdot) = P_{[-1,1]^N}$

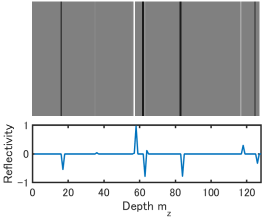
7: $n \leftarrow n + 1$

8: **end while**

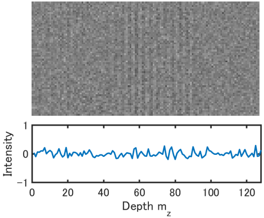
Generalized for generative process, $\mathbf{\Psi}$, from the original

S. Ono, "Primal-dual plug-and-play image restoration," IEEE Signal Processing Letters, vol.24, no.8, pp.1108–1112, Aug. 2017.

Simulation



(a) Source **u** of size
$64 \times 64 \times 128$ voxels

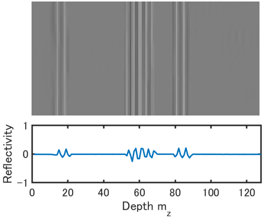


(b) Observation **v**
PSNR: 21.50 dB

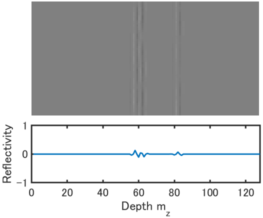
(Top) YZ slice . (Btm) Z direction Seq.

- Z position of reflective XY surfaces are randomly generated.
- Reflection ratio of each surface is randomly set in $[-1, 1]$.
- AWGN with zero mean and $\sigma_{\mathrm{w}} = 0.1$ is assumed.

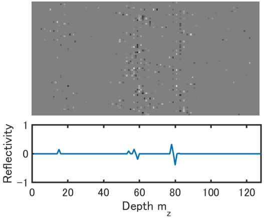
Simulation



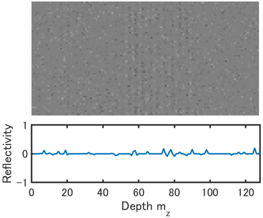
(a) PDPnP w **D**:IDNT & $\mathfrak{G}_{\mathcal{R}}$:BM4D
PSNR: **27.31 dB**



(b) PDPnP w **D**:UDHT & $\mathfrak{G}_{\mathcal{R}}$:SFTH
PSNR: 26.32 dB

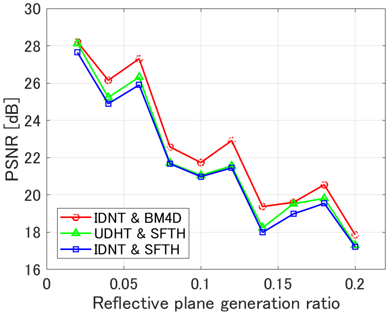


(c) PDPnP w **D**:IDNT & $\mathfrak{G}_{\mathcal{R}}$:SFTH
PSNR: 25.90 dB



(d) BM4D Denoise (Ref.)
PSNR: 22.73 dB

Simulation



Dictionary	
IDNT	Identity
UDHT	Undecimated Haar Trans.

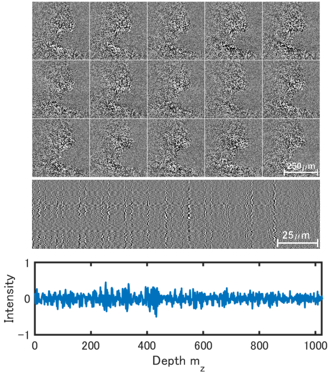
Gaussian Denoiser	
SFTH	Soft-thresholding
BM4D	[M. Maggioni, TIP2013]

- PSNR vs Reflective surface generation ratios
- MSEs of 5 trials are averaged and converted to PSNR.

PDPnP with BM4D shows the best performance.
The significance of dictionary is also indicated with less computation.

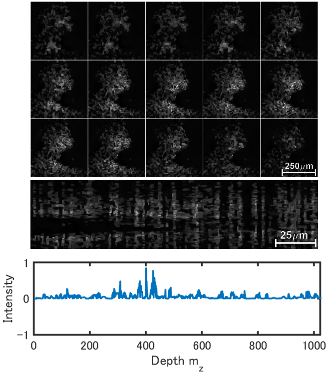
Restoration experiment of sensory epitherlium

Observation through MS *en-face* OCT ($244 \times 240 \times 1024$ voxels)



(a) Observation $\mathbf{v}$

Guinea pig inner ear sensory epithelium



(b) Estimation $|\hat{\mathbf{u}}|$

PDPnP with BM4D, ♯Iter. 200

(Top) 15 XY slices. (Mid) YZ Slice. (Btm) Z Seq.

Conclusions

- Proposed to apply PDPnP to OCT data restoration
  - Realized removal of noise and interference fringe simultaneously.
  - No matrix inversion is required.
  - Hard constraint is available.
  - Arbitrary Gaussian denoiser can be pluged in.
- Verified the significance through
  - Simulation for artificial data
  - Experiment on observation via MS *en-face* OCT
- Future works include
  - Tomographic acquisition of vibration
  - Estimation of measurement process $\mathbf{P}$
  - Construction of synthesis dictionary $\mathbf{D}$
  - Examination of appropriate noise model

Acknowledgement

This work is supported by AMED-CREST and JSPS KAKENHI (JP16H03164).