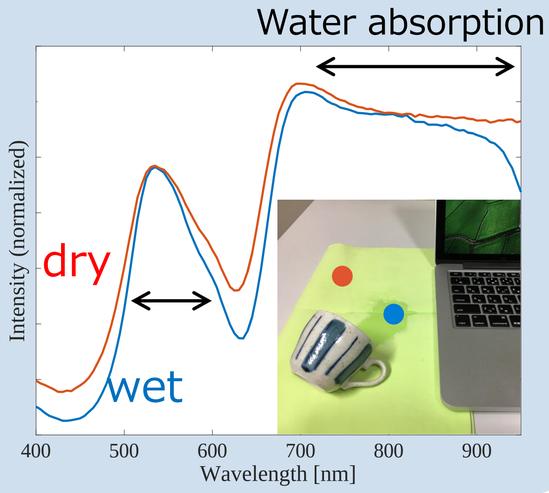
三原色を超えて、光スペクトルからわかること
Wet/Dry? 状態変化に伴う輝度・色変化

どんな研究？

状態の違いによる見えの変化のモデル化
特に、**『濡れている』**状態の見えに着目



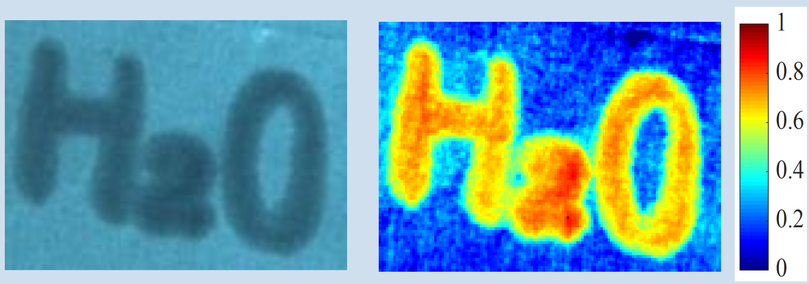
何がわかる？

濡れることによる見えの変化の特徴

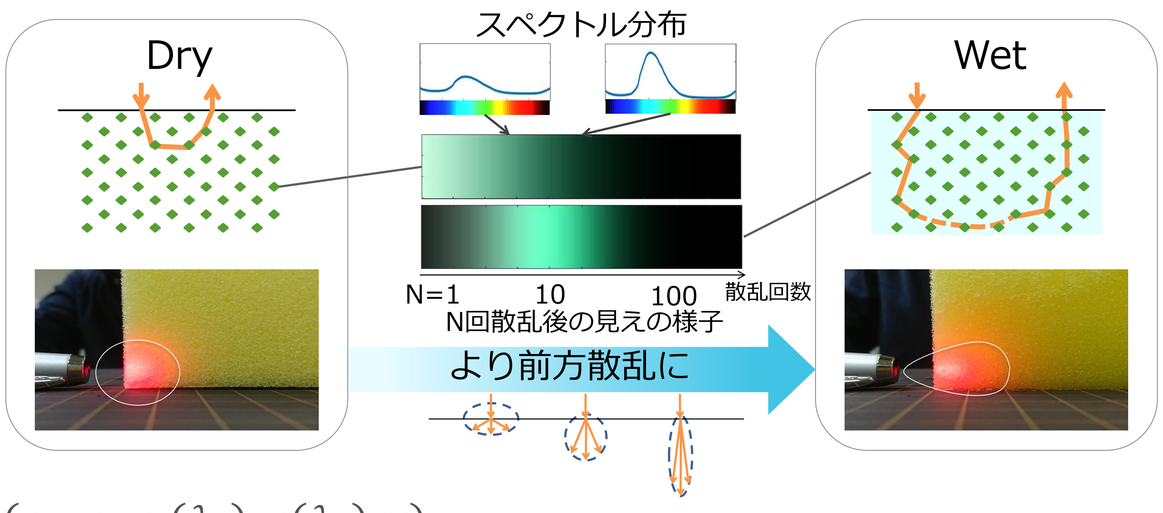
Spectral sharpening　Darkening

- 濡れた表面の見えの**分光モデルの構築**
- 濡れ分布や乾いた状態の色を**一枚の分光画像から復元**

濡れ分布の再現例



濡れた表面の分光モデル



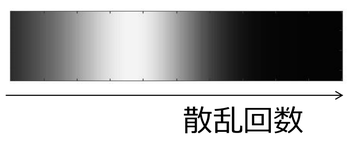
$$I(g_d, g_s, u(\lambda_k), v(\lambda_k), \gamma) = I_0 \sum_n \alpha\left(g_d^{(1-\gamma)} g_s^{\gamma}, n\right) p^{\{n\}}\left(g_d^{(1-\gamma)} g_s^{\gamma}\right) \exp[-r_0(u(\lambda_k)n + v(\lambda_k)\gamma n)]$$

n回散乱した後に光が物体表面に返ってくる割合

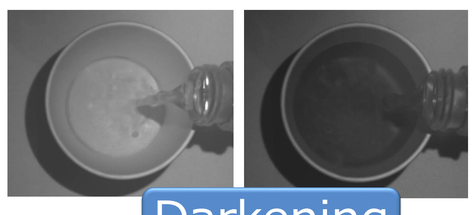
Henyey-Greenstein 位相関数

光路長の伸長

素材や液体の吸収



Spectral sharpening



Darkening

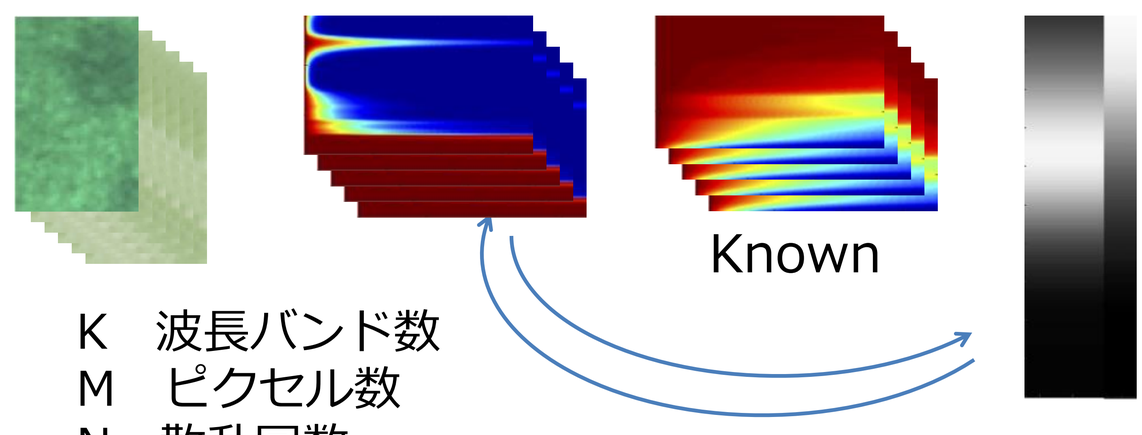
表面の濡れと色の推定

導出した分光モデルに基づいて、濡れや吸収係数等を推定

$$\mathcal{W} = (\ \mathcal{A} \circ \mathcal{B}\ ) * \mathcal{T}$$

Material and liquid absorption

$K \times M$　$K \times N \times M$　$N \times M$



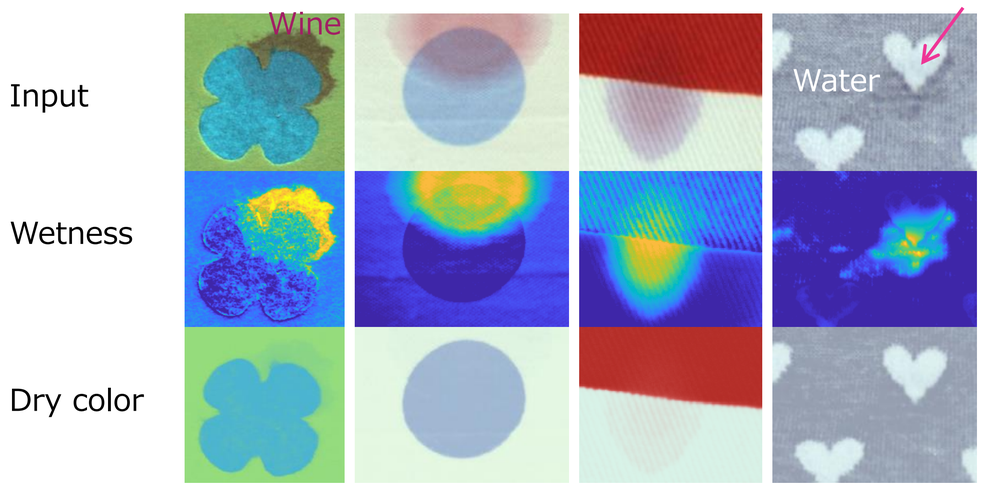
K　波長バンド数
M　ピクセル数
N　散乱回数

各ピクセルにおけるn回散乱光が物体表面に返ってくる割合

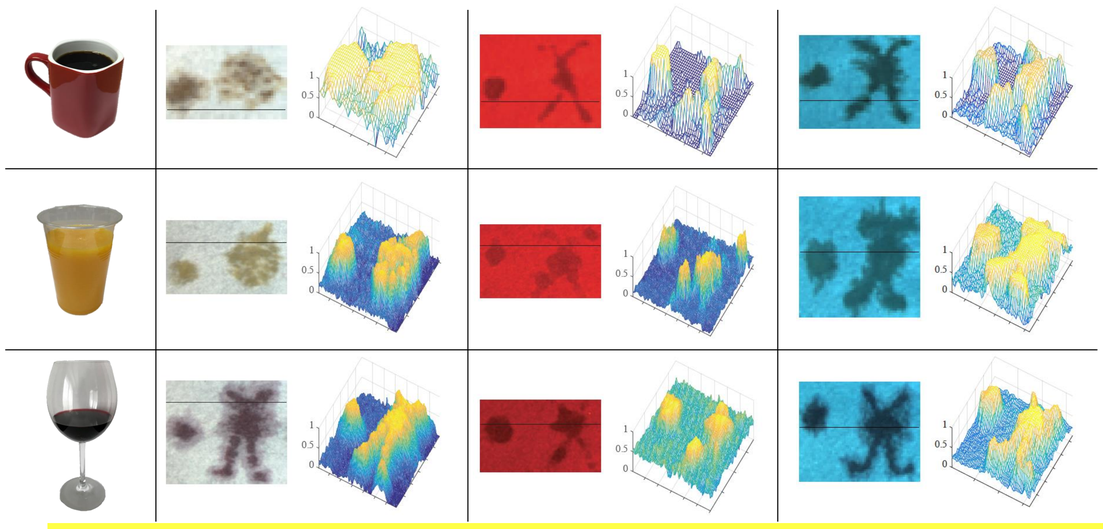
交互最適化によって各パラメータを推定
（テクスチャを含んだシーンの場合は各画素がどの色かも推定）

実験結果

1．濡れと色の推定

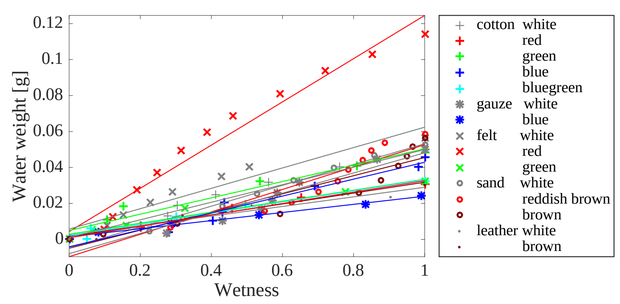


2．異なる液体による濡れの推定



3．定量評価

『濡れ度合い』の正解を『しみ込んだ水の重さ』として計測。推定濡れ度合いとほぼ線形となり、十分な精度を達成



IEEE 2017 Conference on Computer Vision and Pattern Recognition

CVPR July 21-26 HONOLULU 2017

コンピュータビジョン トップ国際会議 Oral採択

NII
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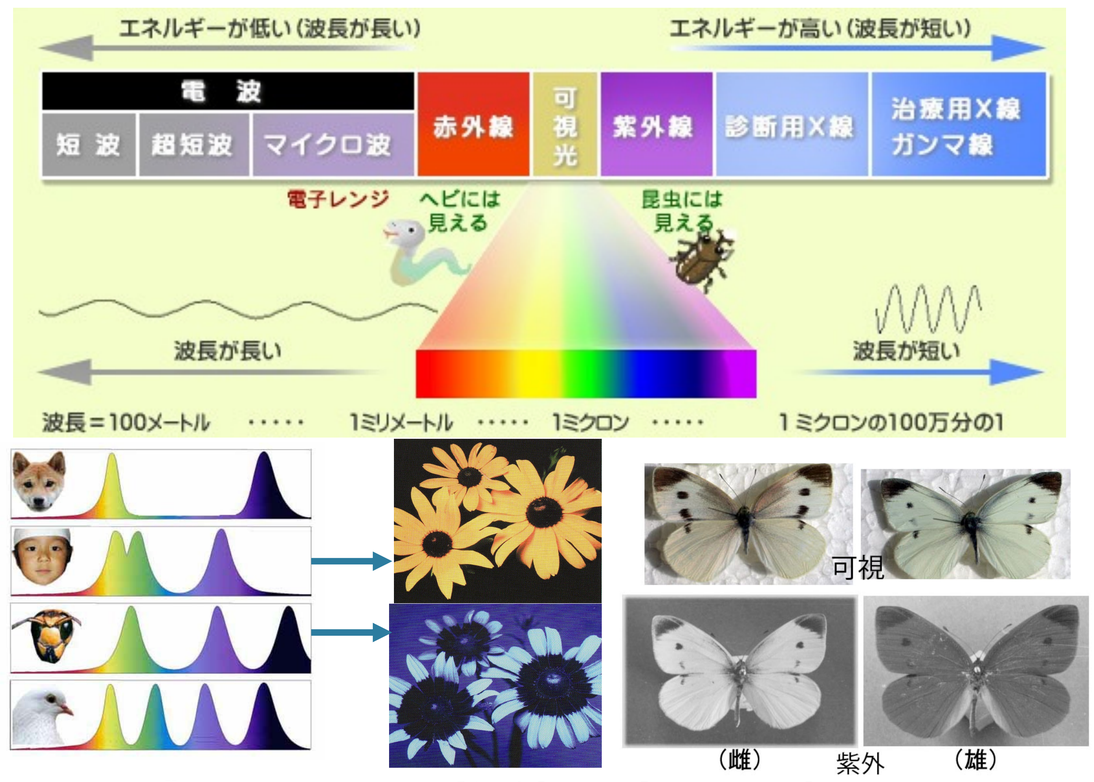
光と画像のモデルからわかること

光学と画像処理による実世界センシング

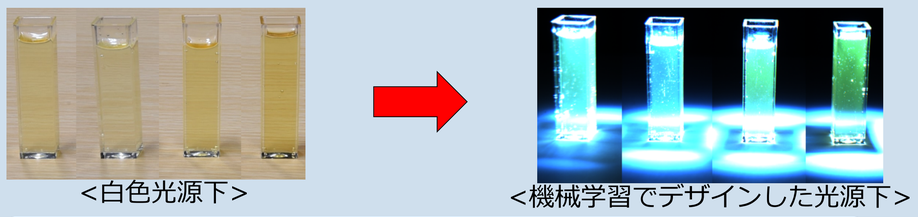
実世界の様々な質感
SHITSUKAN Science & Technology

光を通して観る世界
Hyperspectral Imaging

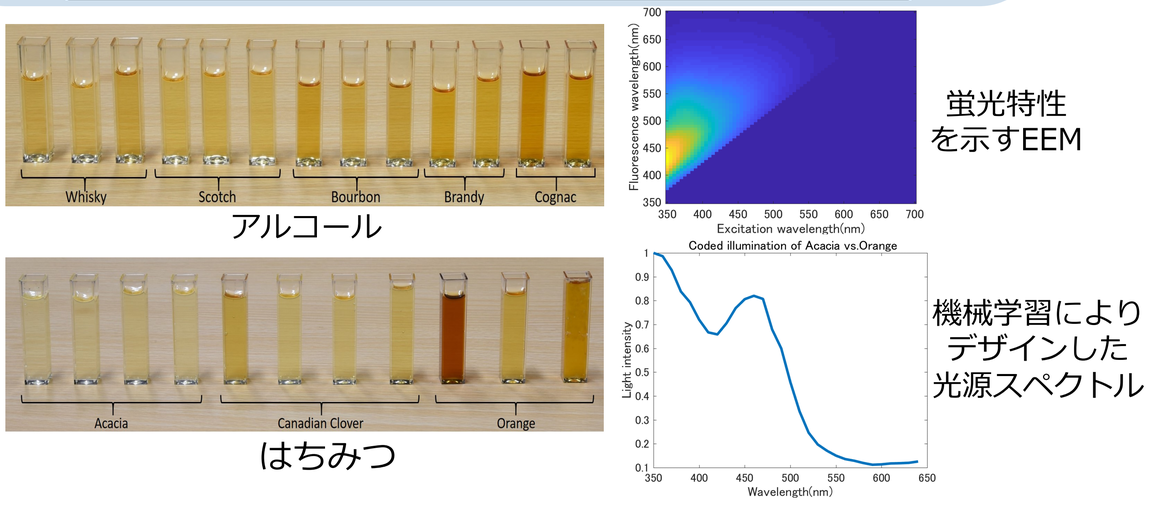


蛍光特性による分類手法
Coded Illumination and Imaging

蛍光発光特性を事前に機械学習することで
商品の種類や産地、異物がないかを識別

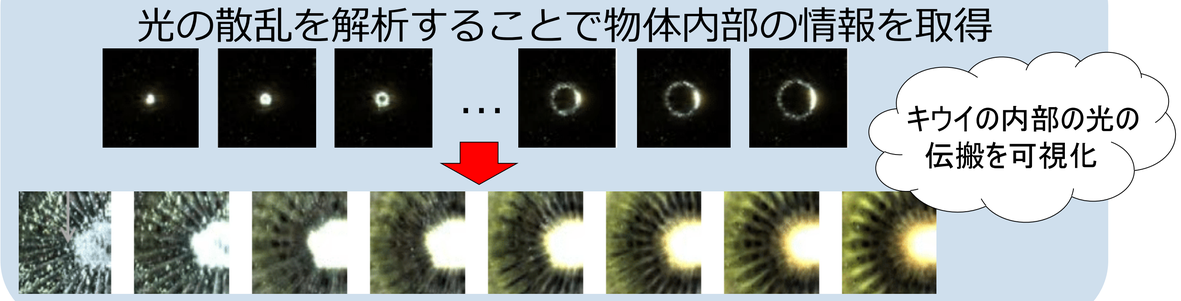


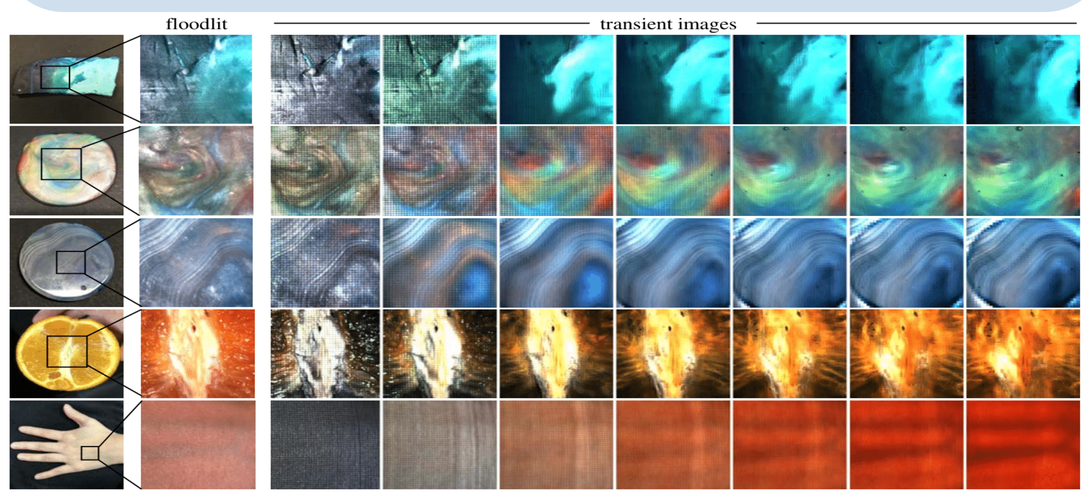
全く同じに色に見えるはちみつが、種類により異なる色に！



リングライトによる物体内部の可視化
Variable Ring Light Imaging

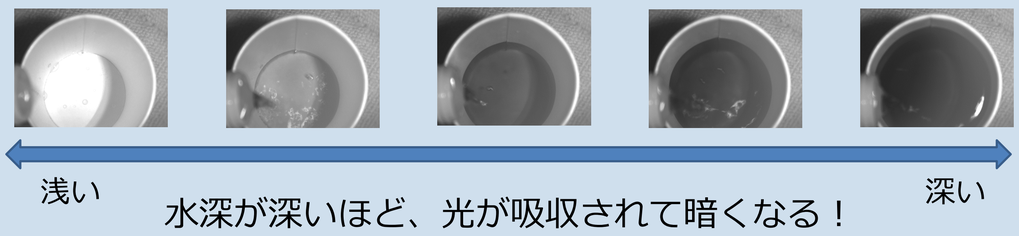
仮想的に様々なサイズのリングライトを照射して
光の散乱を解析することで物体内部の情報を取得



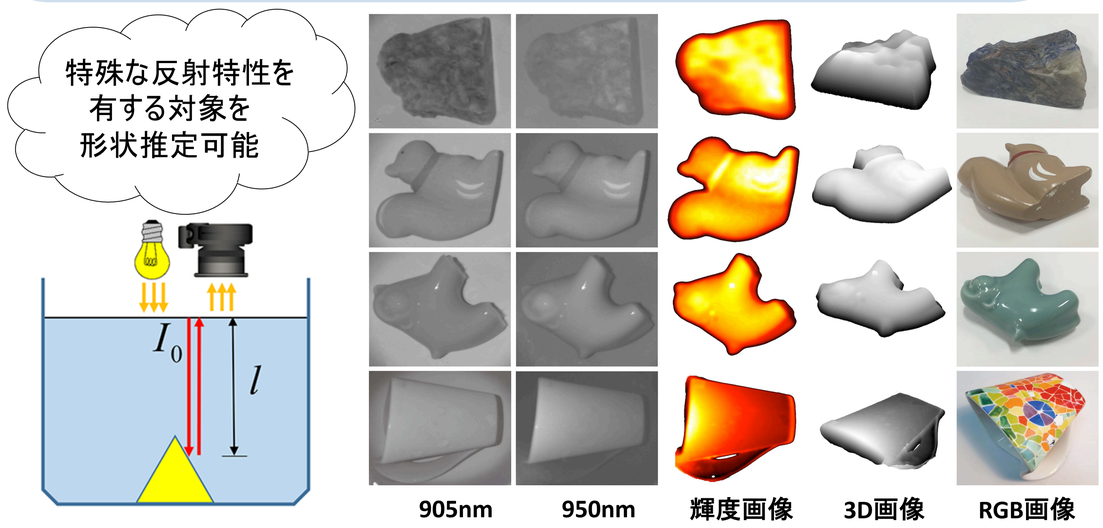


水中における物体の形状推定手法
Shape from Water

近赤外線が水に吸収される特性を利用して
対象物体の三次元形状を推定

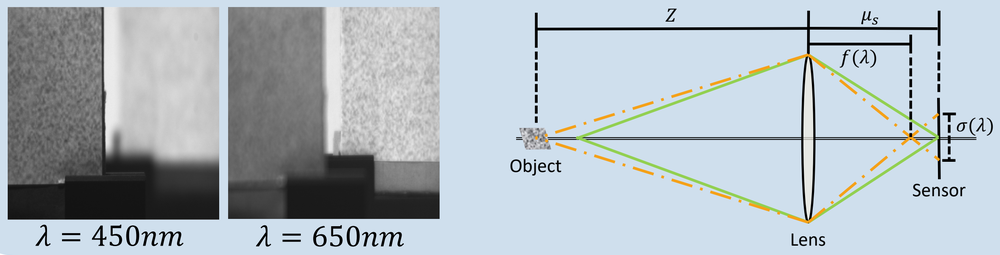


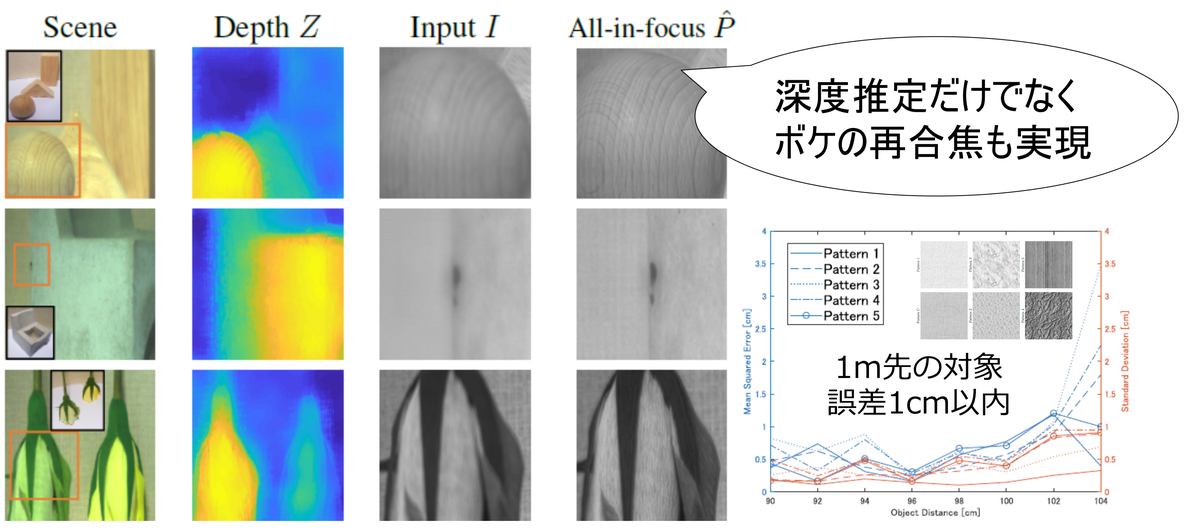
水深が深いほど、光が吸収されて暗くなる！



分光スペクトルと深度情報の同時取得
Depth from Spectral Defocus Blur

レンズの焦点距離の波長依存性を利用して
多波長画像のボケを解析することで深度を推定





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Semi-Supervised Learning for Biomedical Image Segmentation via Forest Oriented Super Pixels(Voxels)

革新的研究開発推進プログラム ImPACT Impulsing Paradigm Change through Disruptive Technologies Program

NII 大学共同利用機関法人 情報・システム研究機構 国立情報学研究所 National Institute of Informatics

慶應義塾 Keio University

九州大学 KYUSHU UNIVERSITY

Motivation

- Collecting massive biomedical data is easy, but annotating them is expensive as it necessitates specific knowledge.
- How to predict the pathological region without training data.

Our Solution

Key observation is that the homogeneous connected areas of low con-fidence (Fig.1(b)) tends to confuse the classifier with limited training data.

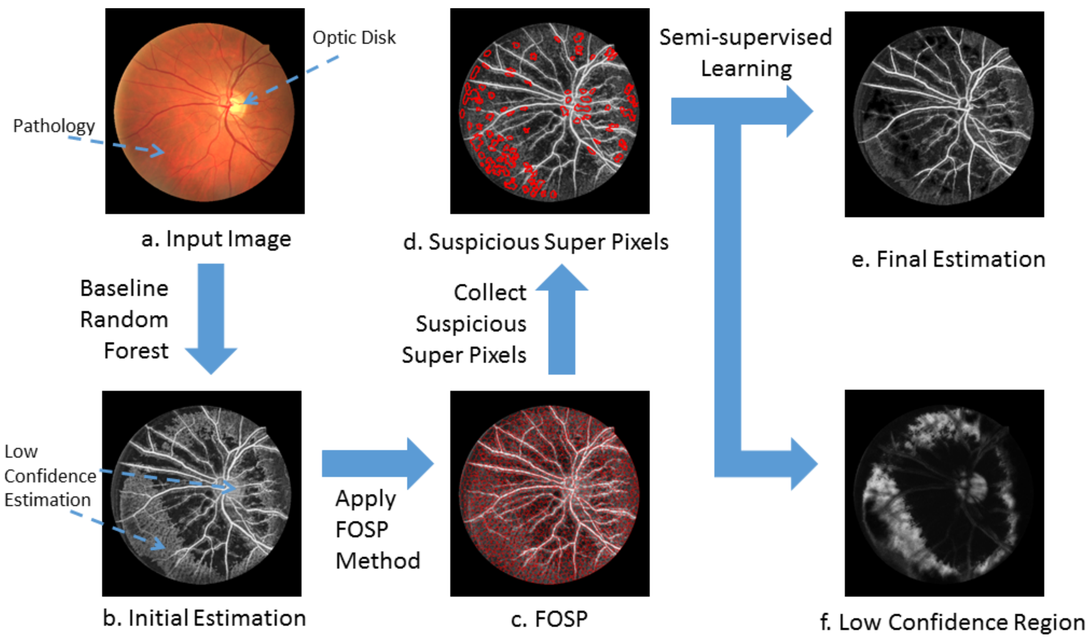


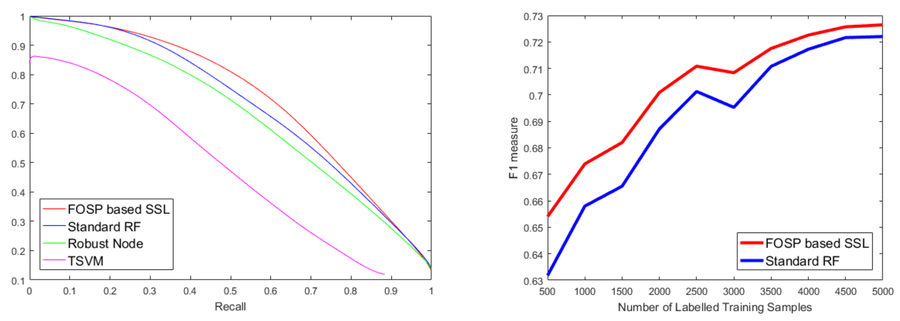
Figure 1: The pipeline.

1. Our method segments the images into super pixels(voxels) (Fig.1(c)) to pick up the low confidence samples.
2. From suspicious super pixels (Fig.1(d)), we train a Random Forest to predict the low confidence areas (Fig.1(f)).
3. By suppressing found low confidence area, our proposed method shows superior performance on challenging 2D retinal and X-ray im-ages and 3D Neuron Data.

Our Key Contribution

Unlike existing methods, such as SLIC[1], based on unsupervised colour space, our Forest Oriented Super Pixels(Voxels) works on the distance defined on forest based code.

Results



PR Curves **F1 vs Labelled Data Size**

Figure 2: Quanatative Comparision on DRIVE dataset.

We evaluate our method on the retinal dataset DRIVE, X-ray hand image and 3D Big Neuron Challenge[4]. We compare the segmenta-tion performance with two semi-supervised method: TSVM[2], Ro-bust Node Random Forest[3]. All of the methods are trained with only 500 labelled samples.

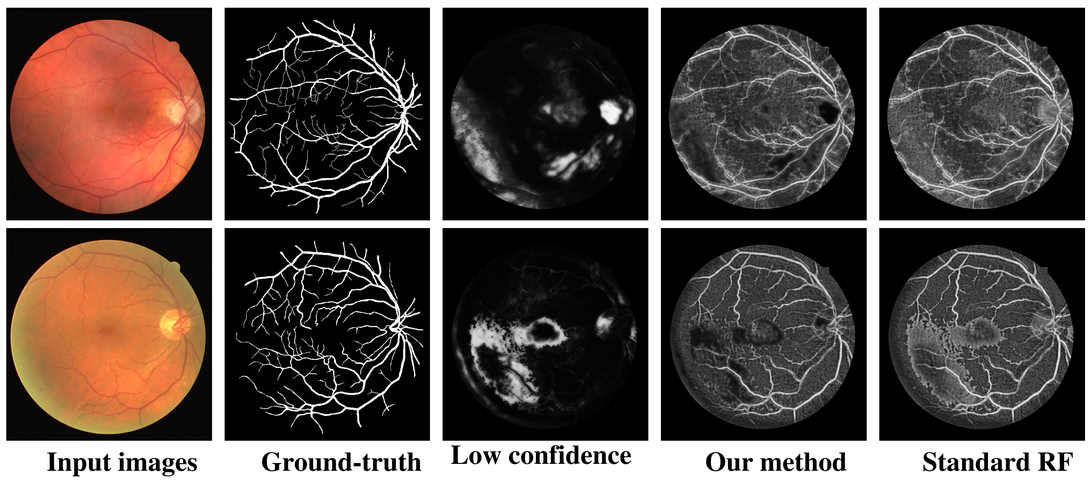


Figure 3:

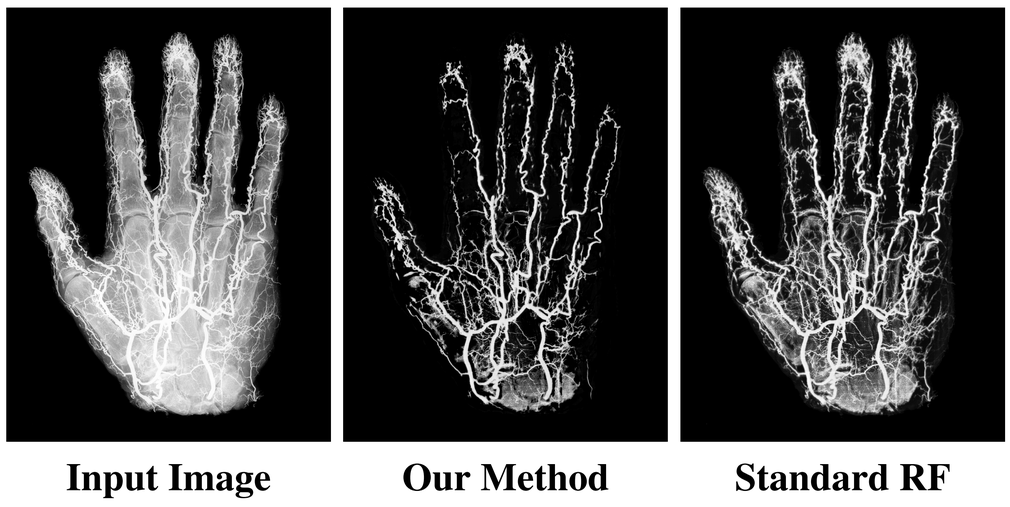


Figure 4: X-ray images of hand.

Figure 5: BigNeuron dataset [4].

Our Contributions

1. We propose a novel Forest Oriented Super Pixels (Voxels) to capture the complementary information of random forest, offering an advan-tage in the random forest based semi-supervised learning.
2. Our super pixel (voxel) is discriminant to segmentation task.
3. We succeed in unsupervised prediction of the suspicious regions i.e. pathological regions that would otherwise confuse the classifier.
4. We have made our source code public available at GitHub, please check https://github.com/lingucv/ssl_superpixels

Figure 6: Please scan our QR

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[4] Hanchuan Peng, Michael Hawrylycz, Jane Roskams, Sean Hill, Nelson Spruston, Erik Meijering, and Giorgio A. Ascoli. Bigneuron: Large-scale 3d neuron reconstruction from optical microscopy images. *Neuron*, 2015.

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