WHEN DATA MET TOOL Make Something New!

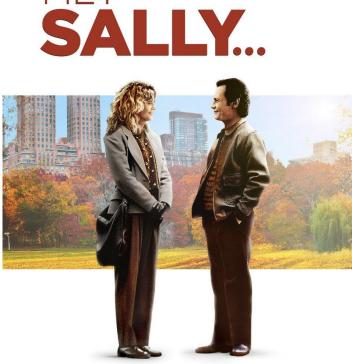


TOMOCUBE AI Team Leader hsmin@tomocube.com/min6284@gmail.com



TOOL (AI)

WHEN DATA (TOMOCUBE HOLOTOMOGRAPHY) MET



WHEN

MET

HARRY



Diatom

Fission yeast

Bacteria (*E.coli*)



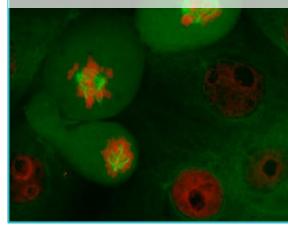


Ostreopsis

Bright-field microscopy (17th century)



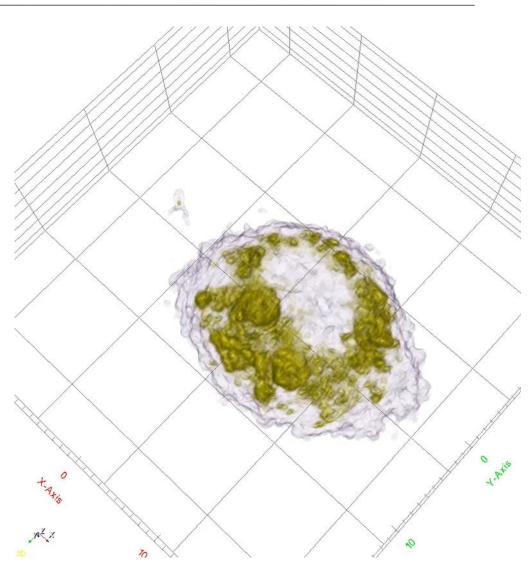
Fluorescence (Nobel Prize, 2008)



Phase contrast (Nobel Prize, 1953)

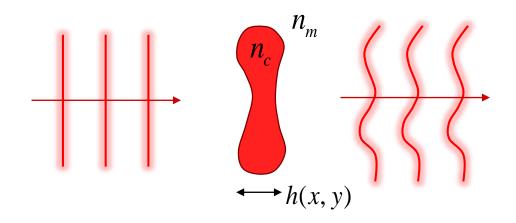


HoloTomography (HT) (Tomocube*,* 2016)

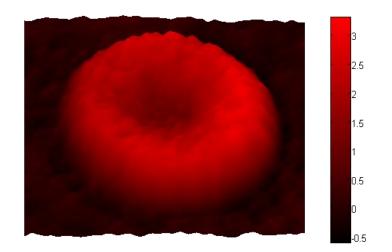


Holographic imaging

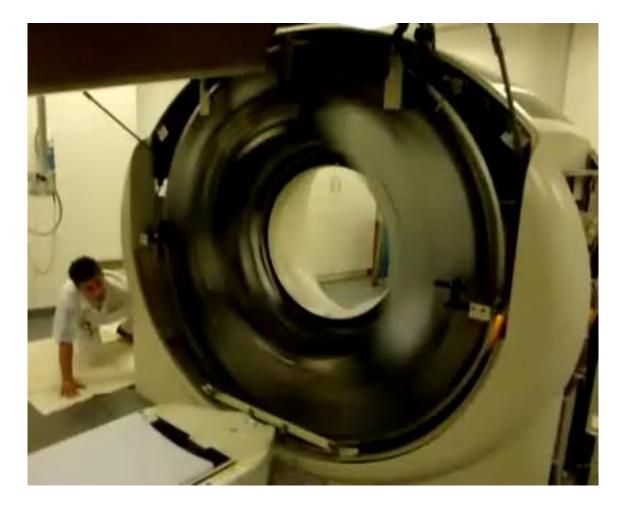
Refractive index : intrinsic optical contrast

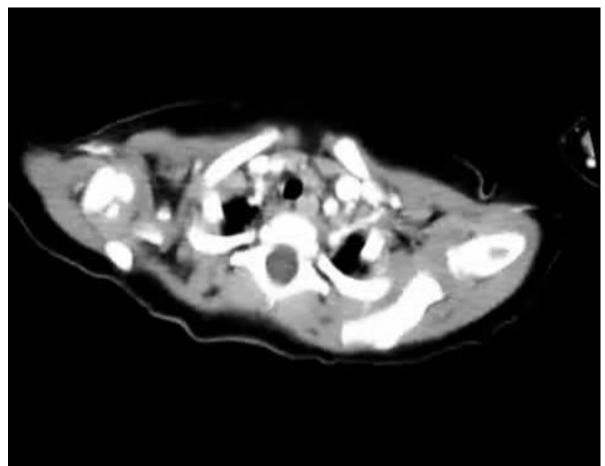


label-free quantitative bioimaging



CT of Cell?





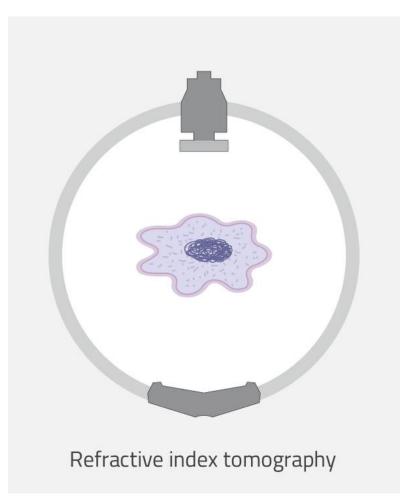


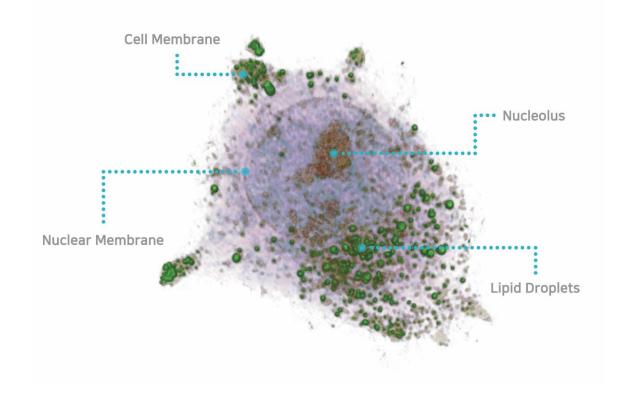
X-ray CT (computed tomography)



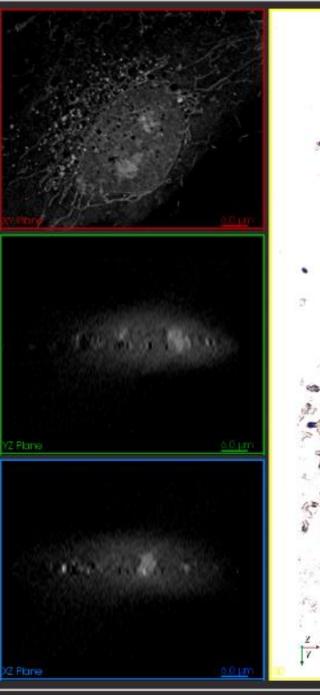
Computed tomography

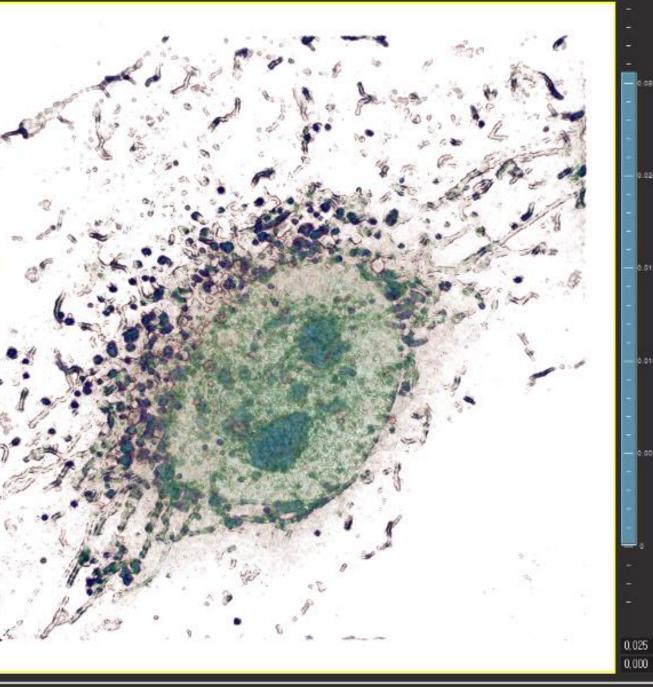


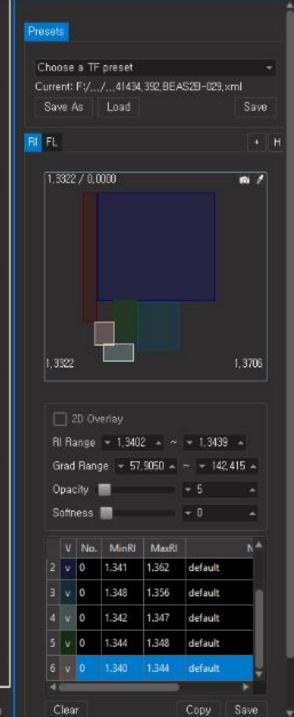




Hepatocyte







- 5x

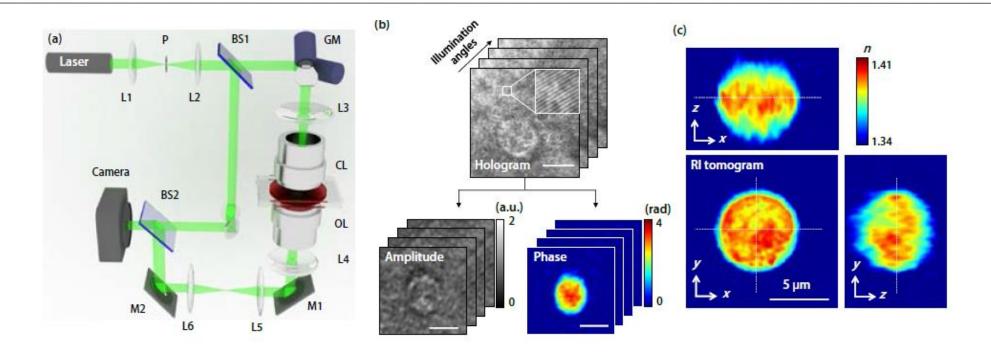
0.025

0.020

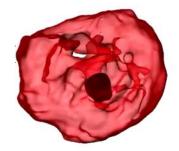
0.015

6.010

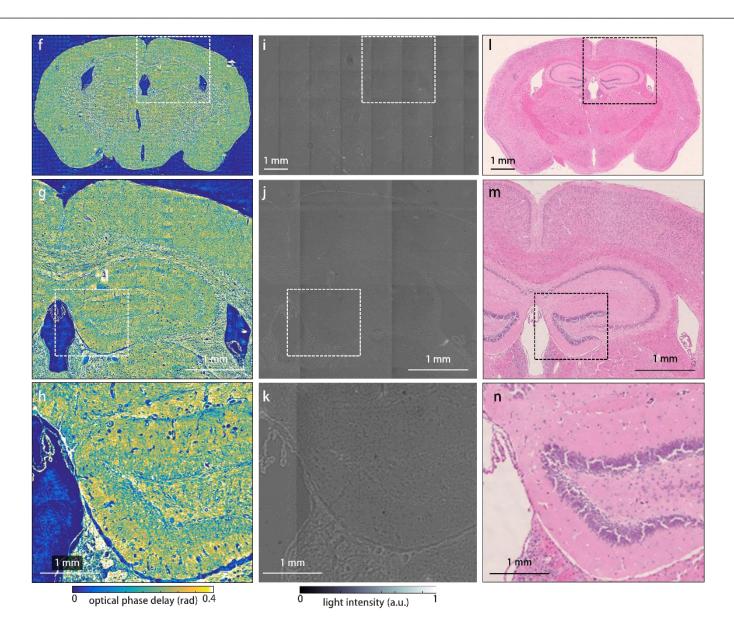
0.005





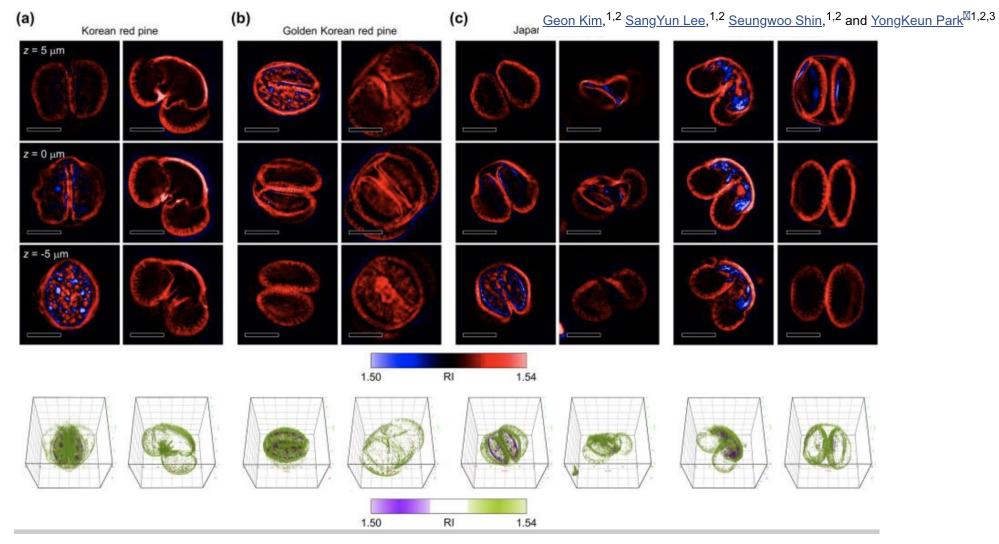






<u>Sci Rep</u>. 2018; 8: 1782. Published online 2018 Jan 29. doi: [<u>10.1038/s41598-018-20113-w</u>]

Three-dimensional label-free imaging and analysis of *Pinus* pollen grains using optical diffraction tomography



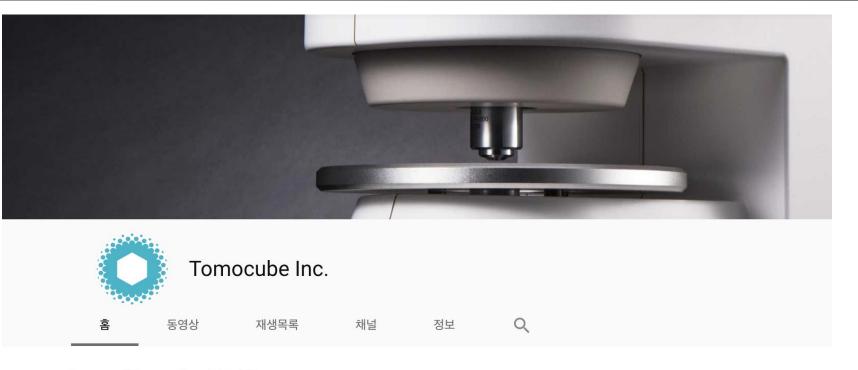


Image of the week 모두 재생





Introducing 3D Correlative Microscopy, the HT-2

3D holotomography meets **3D fluorescence microscopy**

Start from 3rd of July 2017

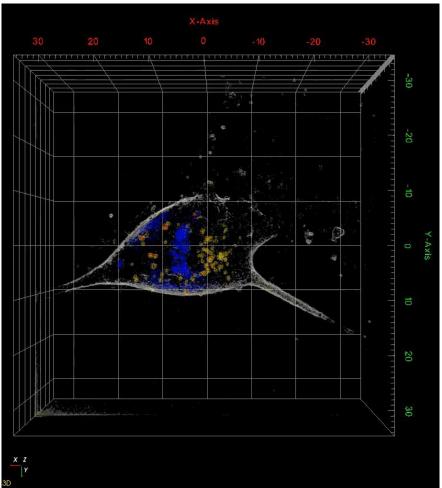
"Tomocube is pleased to announce a **new HT-2 system** for holotomography with **3D fluorescence** imaging capability."

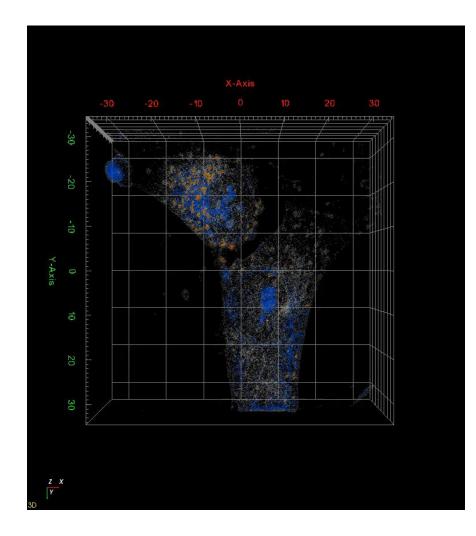


Tomocube, Inc.

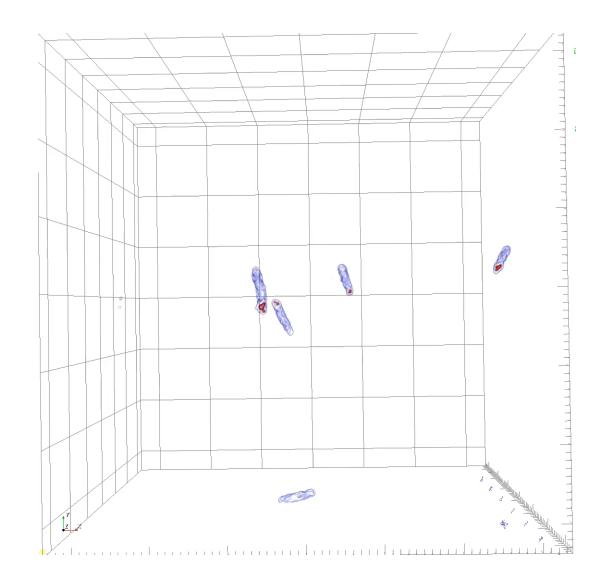
2F, 48, Yuseong-daero 1184beon-gil, Yuseong-gu, Daejeon, Korea T +82-42-863-1100 info@tomocube.com www.tomocube.com

Stem Cell (Wharton jelly5)

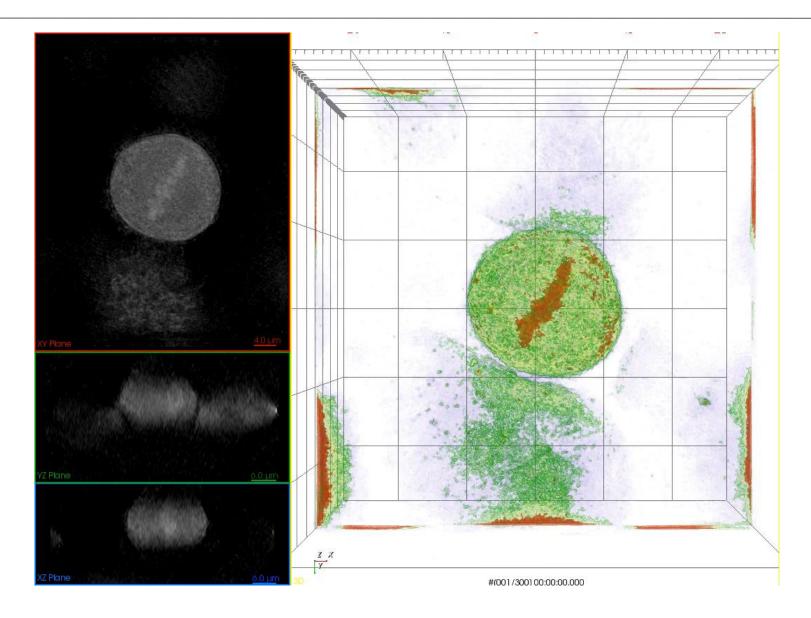


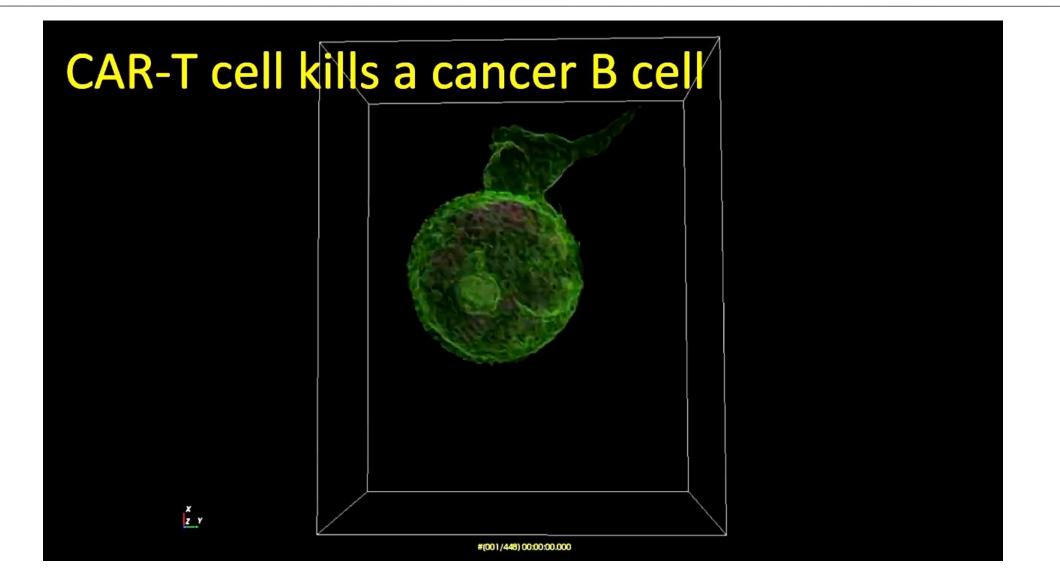


Bacterial division



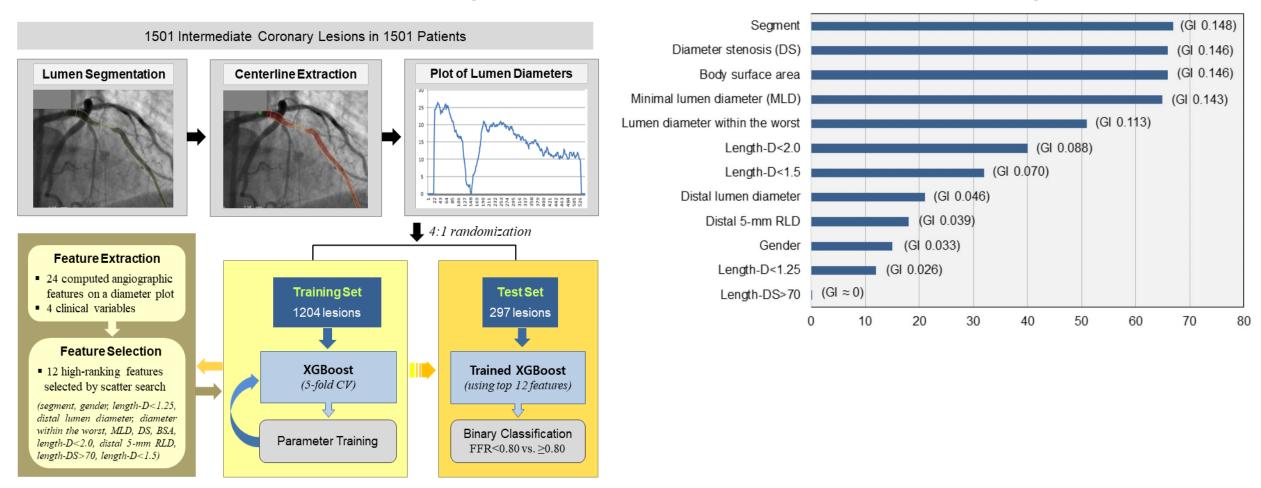
Cell Division





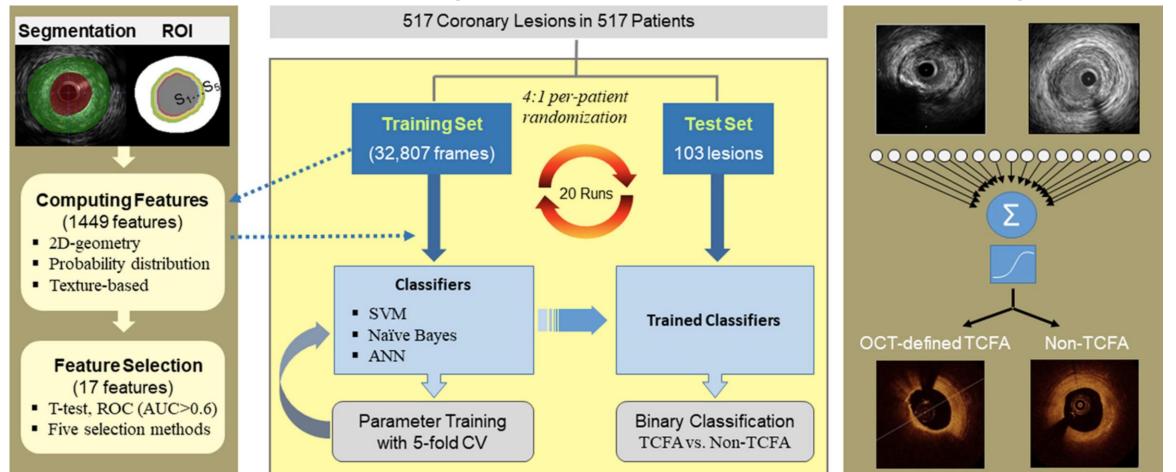


What we did – classification (conventional ML + feature extraction)



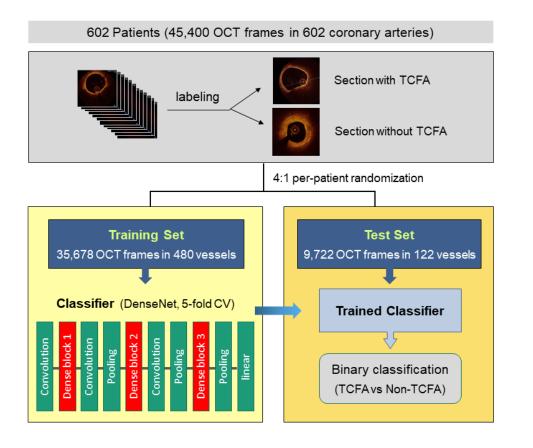
JAHA: Journal of the American Heart Association

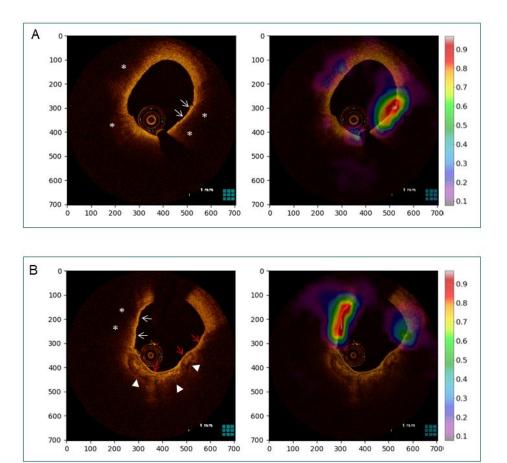
What we did – classification (conventional ML + feature extraction)



Atherosclerosis

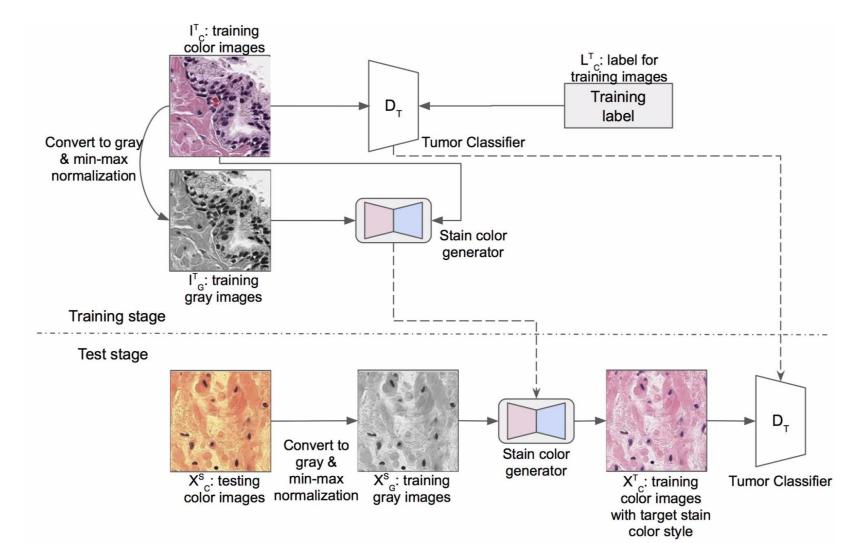
What we did – classification (deep learning)





Under revision – European Heart Journal - Cardiovascular Imaging

What we did – translation, generation (GAN, encoder-decoder structure)



What we did – translation, generation

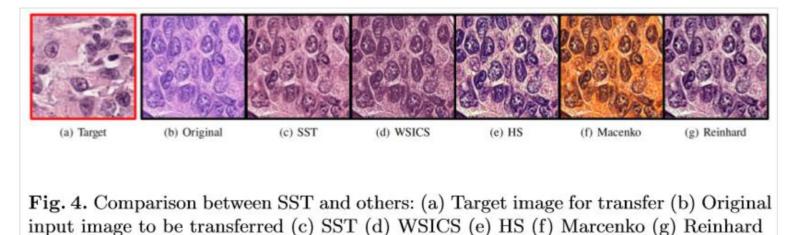
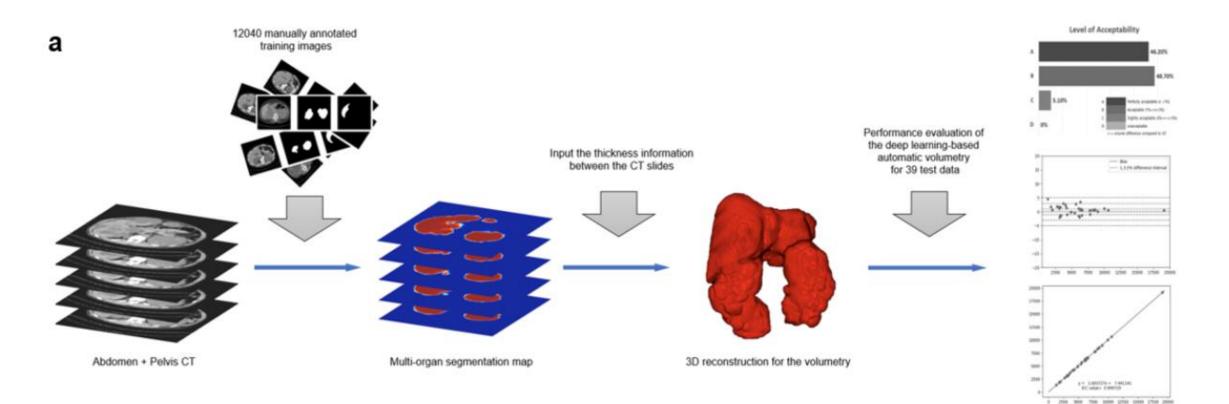


Table 1. Performance of CNNs based tumor classifiers among different stain color normalization methods. SST model shows classification improvement compared to naive application to original (untransferred image) and outperforms the others.

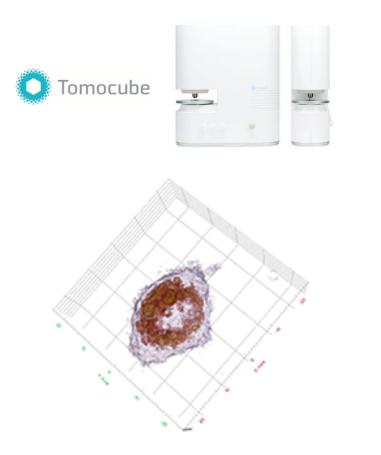
Model	Target	Original	SST	Reinhard	Macenko	HS	WSICS
AUC	0.9760	0.8900	0.9185	0.5611	0.7169	0.4245	0.6408
Precision	0.9114	0.8098	0.8440	0.6114	0.6983	0.4987	0.5989
Recall	0.9126	0.8111	0.8460	0.6119	0.6956	0.4986	0.5957
Specificity	0.9583	0.8014	0.8371	0.5471	0.6500	0.4162	0.6010

What we did – detection, segmentation (3D Unet + attention)



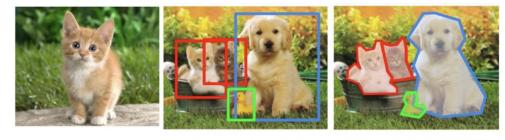
WHAT WE CAN DO?

What tomocube see



What AI can

Classification, detection, segmentation



CAT CAT, DOG, DUCK CAT, DOG, DUCK

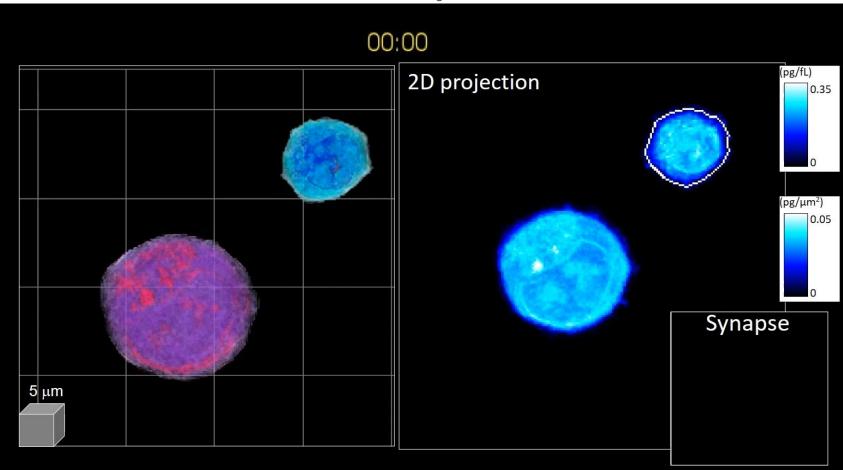
Translation, Generation



WHAT WE CAN DO? – [3D holography + Segmentation] for finding new marker

Deep-learning based three-dimensional label-free tracking and analysis of immunological synapses of chimeric antigen receptor T cells

Moosung Lee, Young-Ho Lee, Jinyeop Song, Geon Kim, YoungJu Jo, HyunSeok Min, Chan Hyuk Kim, YongKeun Park

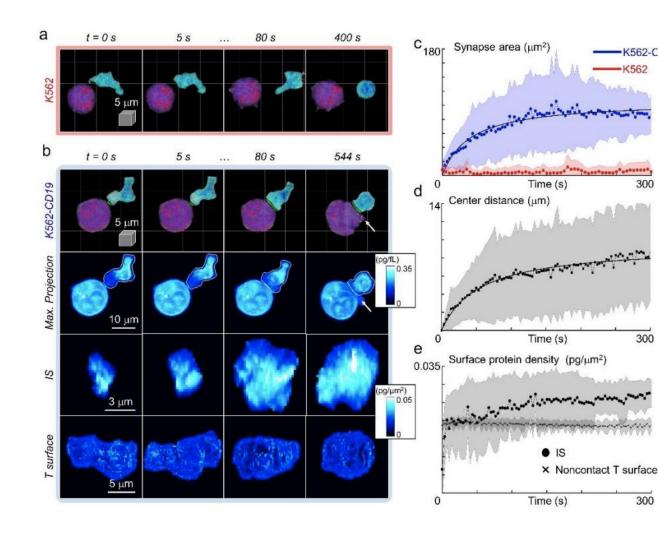


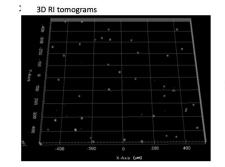
Posted February 04, 2019.

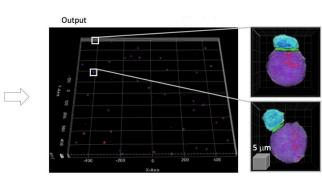
Download PDF

Supplementary Material

WHAT WE CAN DO? – [3D holography + Segmentation] for finding new marker







WHAT WE CAN DO? – [3D holography + translation] for data improvement

Research Article

Vol. 27, No. 4 | 18 Feb 2019 | OPTICS EXPRESS 4927

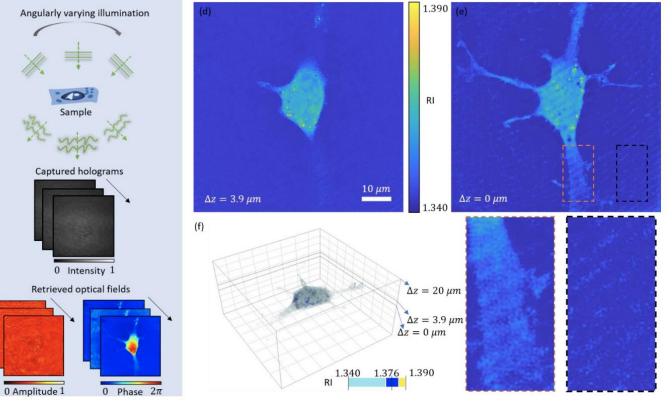
(b)

(c)

Optics EXPRESS

Cycle-consistent deep learning approach to coherent noise reduction in optical diffraction tomography

GUNHO CHOI,^{1,6} DONGHUN RYU,^{2,3,6} YOUNGJU JO,^{1,2,3,5} YOUNG SEO KIM,^{1,2,4} WEISUN PARK,^{1,2,3} HYUN-SEOK MIN,¹ AND YONGKEUN PARK¹



Optics Express, (2019) •https://doi.org/10.1364/OE.27.004927

Fig. 1. Coherent noise problem in optical diffraction tomography (ODT). (a-b) The ODT employs angularly varying illumination to capture off-axis holograms. (c) Each complex optical field is reconstructed from the obtained holograms. (d) 2D sliced image of 3D reconstructed tomogram at $\Delta z = 3.9 \,\mu m$ e) 2D sliced image of 3D reconstructed tomogram at focus $\Delta z = 0 \,\mu m$ corrupted with the coherent noise. (f) 3D rendering of the whole reconstructed tomogram.

WHAT WE CAN DO? – [3D holography + translation] for data improvement

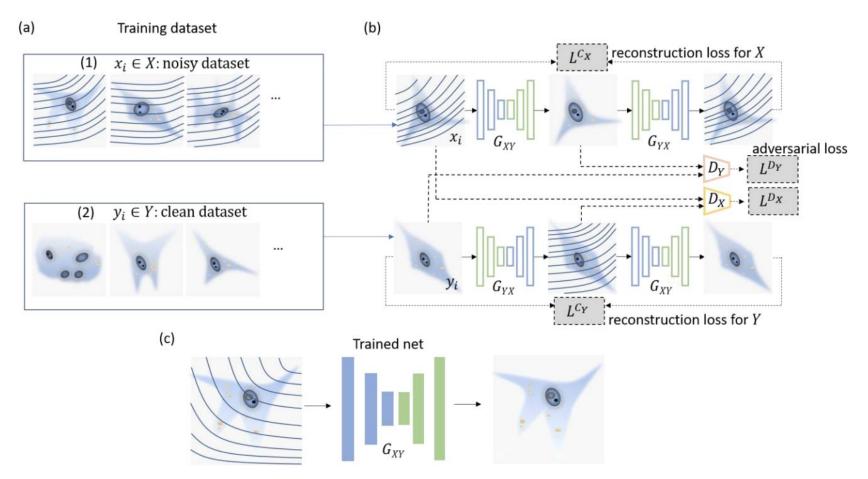


Fig. 2. Overview of the present network for de-noising: training and testing (a) Two classes of dataset for training were prepared. $x_i \in X$: noisy tomogram and $y_i \in Y$: clean tomogram. (b) Training process of the proposed network. G_{XY} : Generator that maps x to y. G_{XX} : Generator that maps y to x. D_y : Discriminator to determine if given input is a generated clean image from G_{XY} or a real data y. D_X : Discriminator to determine if given input is a generated noisy image from G_{YX} or a real data x. L^{D_Y} : Adversarial loss for D_Y . L^{D_X} : Adversarial loss for y. (c) Trained network, G_{XY} removes the coherent noise of 2D sliced tomogram.

WHAT WE CAN DO? – [3D holography + translation] for data improvement

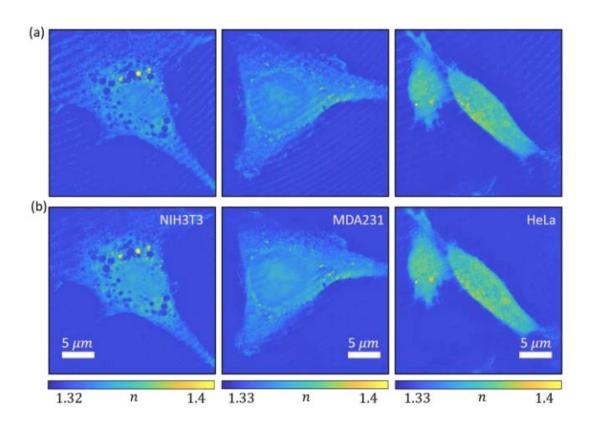


Fig. 5. Experimental validation of the present method. Tomograms of NIH3T3, MDA231, and HeLa (a) in the presence of coherent noise, in the shape of the fringe pattern and (b) after coherent noise removal using our deep neural network.

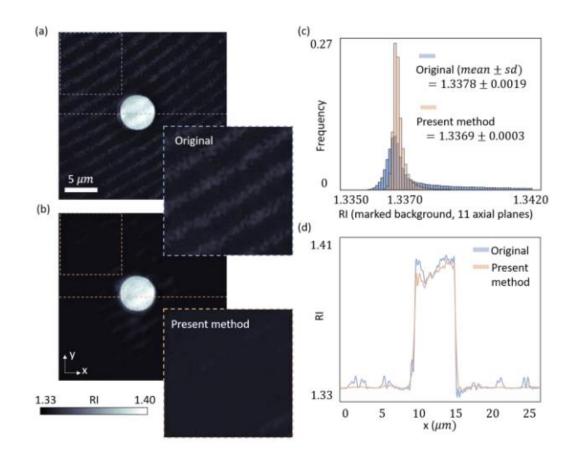
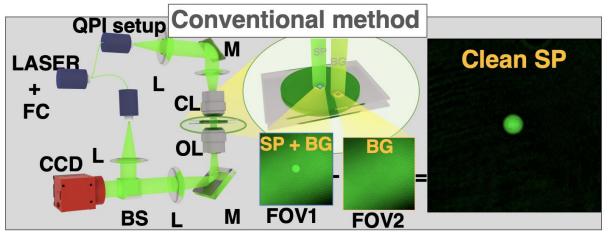


Fig. 4. Quantitative analysis of the proposed network. (a) Original tomogram of the silica microbead degraded by the coherent noise. (b) Tomogram denoised via our method. (c) 2D tomogram slices in the background region (number of slices = 11), marked by top-left corner box, acquired in the axial direction; the RI distributions are shown for comparison to highlight the denoising effect. (d) Line profiles along the horizontal way are visualized.

WHAT WE CAN DO? – [3D holography + classification] for robust imaging

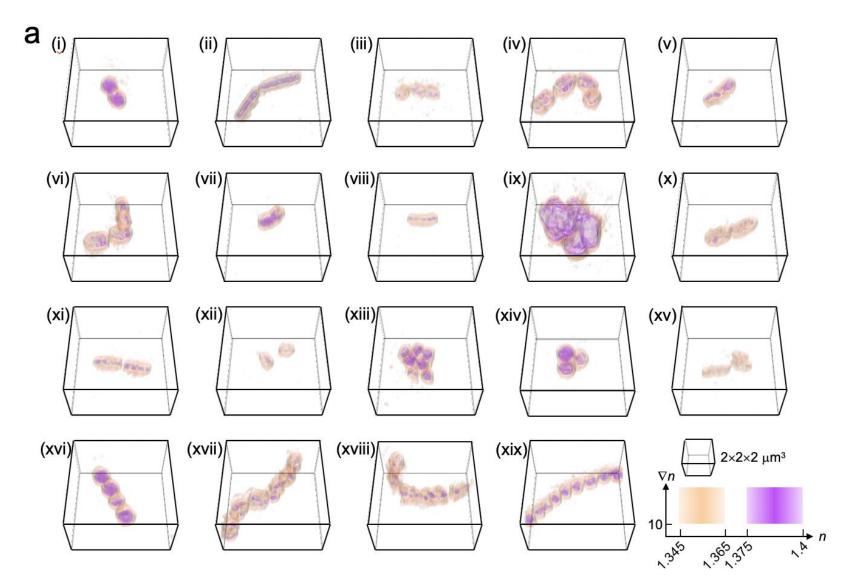
Deep Learning Aberration Compensation in Quantitative Phase Imaging

Taean Chang¹, YoungJu Jo^{1,2}, Hyun-Seok Min², Gunho Choi² and YongKeun Park ^{1,2,*} ¹Department of Physics, Korea Advanced Institute of Science and Technology (KAIST), Daejeon 34141, Republic of Korea ²Tomocube Inc., Daejeon 34051, Republic of Korea *vk.park@kaist.ac.kr



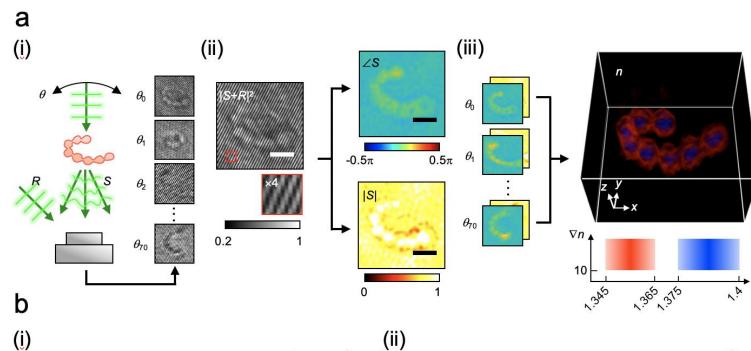
2-Channel Input x 2-Channel Output G(x) Ground Truth y 2-Channel Output G(x) Gr

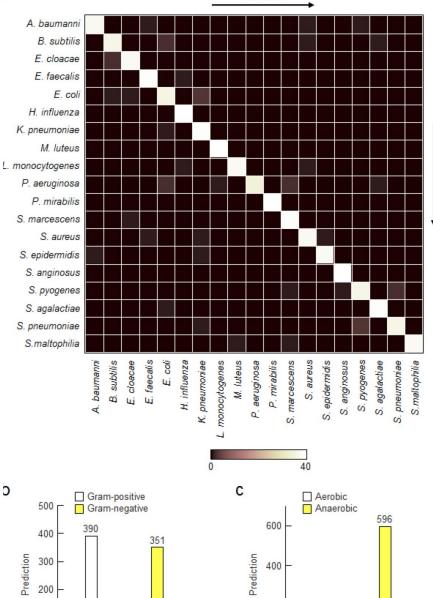
WHAT WE CAN DO? – [3D holography + classification] for diagnosis



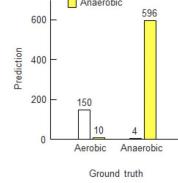
To be submitted

WHAT WE CAN DO? -[3D holography + classification] for diagnosis



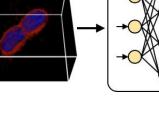


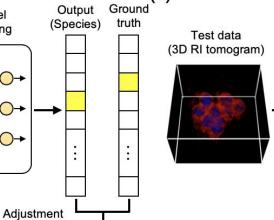
Prediction

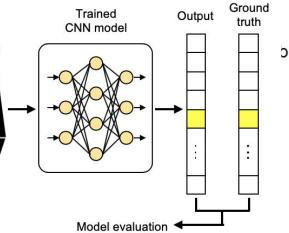


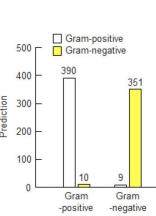
truth

CNN model under training Training data (3D RI tomogram)





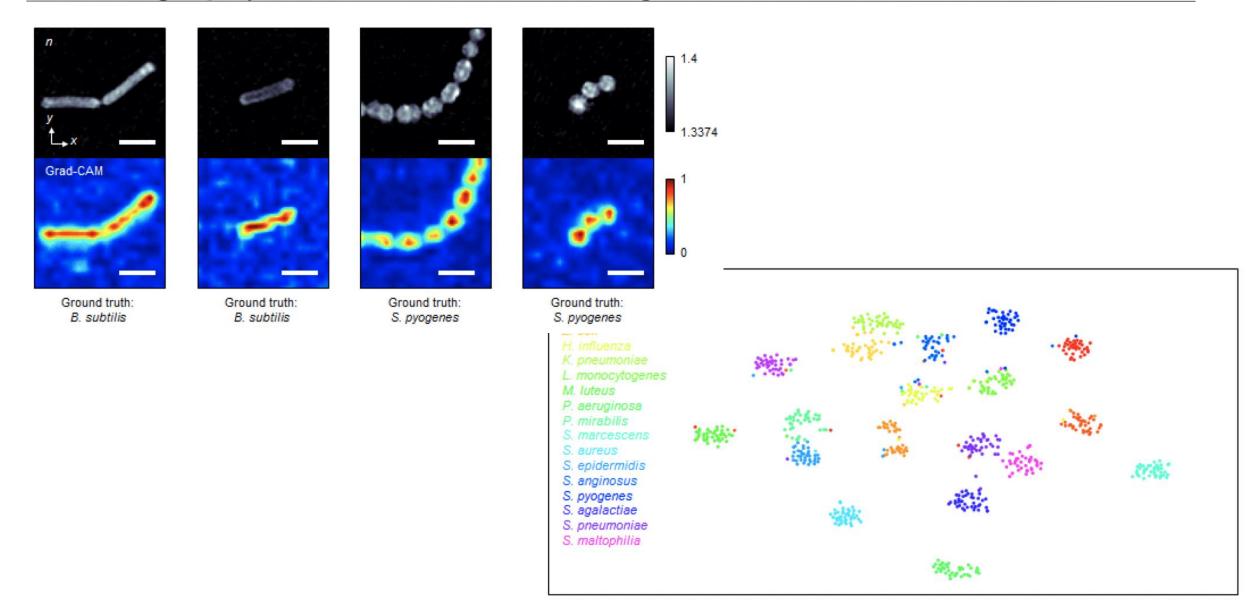




Ground truth

а

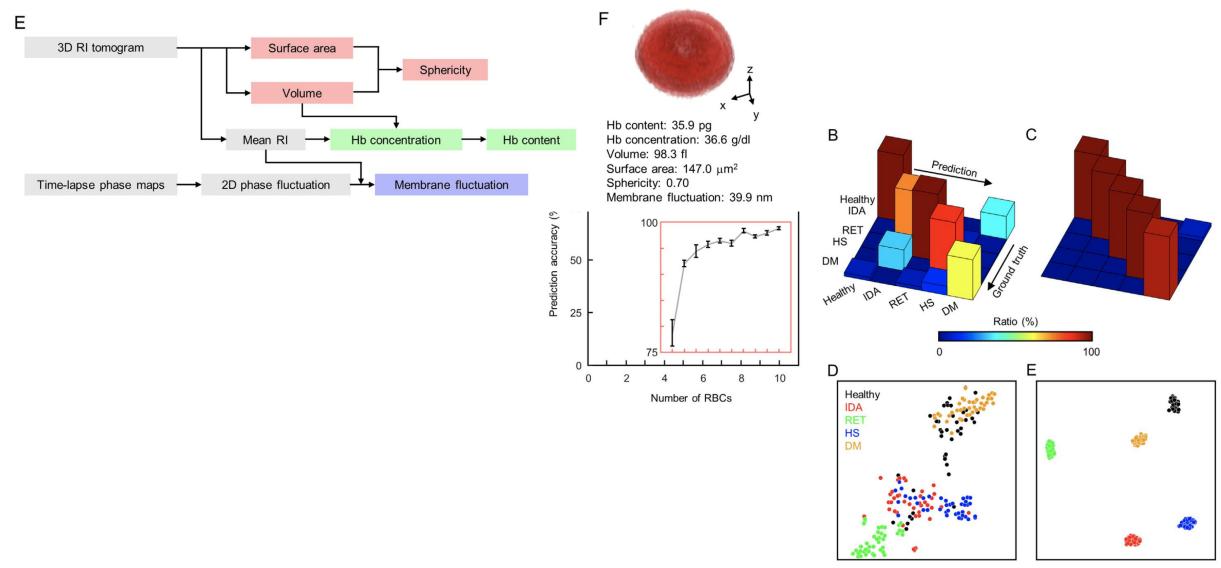
WHAT WE CAN DO? – [3D holography + classification] for diagnosis



WHAT WE CAN DO? – [3D holography + classification] for diagnosis

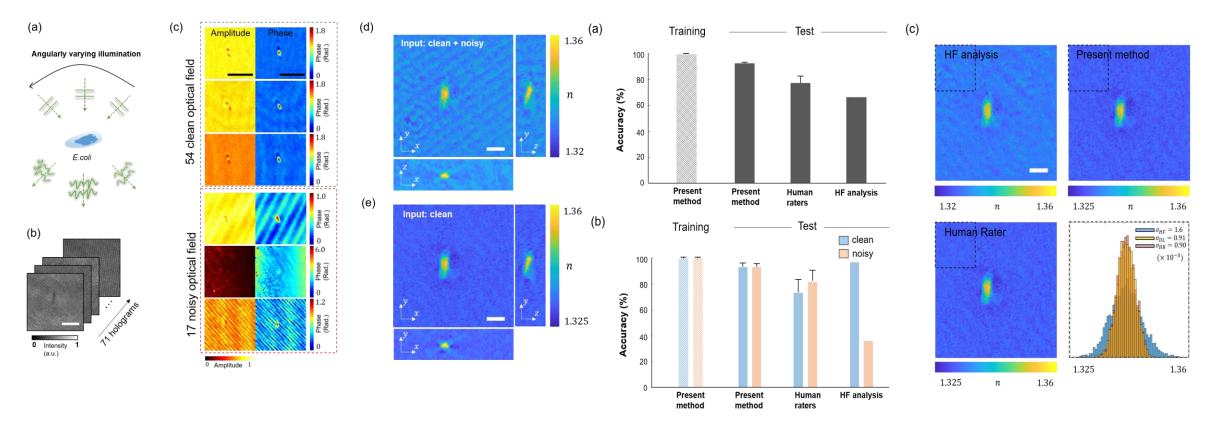
	Antiserum test	Culture and susceptibility test	DNA microarray	Real-time PCR	Proposed method
Time	Hours	Hours to days	Days	Hours	Minutes
Manual analysis	Required	Required	Required	Required	Not required
In vitro culture	Not required	Required	Not required	Not required	Not required
Specialized biochemical agents	Required	Optional	Required	Required	Not required
Sub-species discrimination	Capable	Capable on condition	Capable	Capable	Undetermined

WHAT WE CAN DO? – [3D holography + classification] for diagnosis



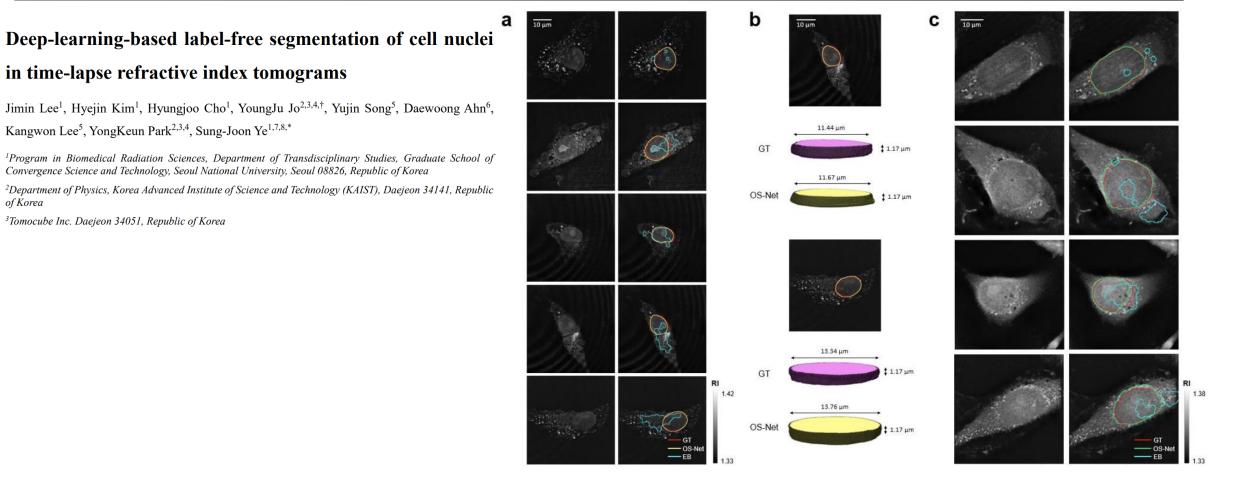
Biosensors and Bioelectronics, (2019)

WHAT WE CAN DO? – [3D holography + classification] for robust imaging



WHAT WE CAN DO? -[3D holography + Segmentation] for finding new marker

of Korea



WHAT WE CAN DO? – [3D holography + Al] for something new



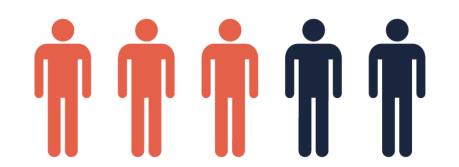


WHEN DATA MET TOOL



HOW WE CAN DO? Everything happened in six months!! With (3+2) members..



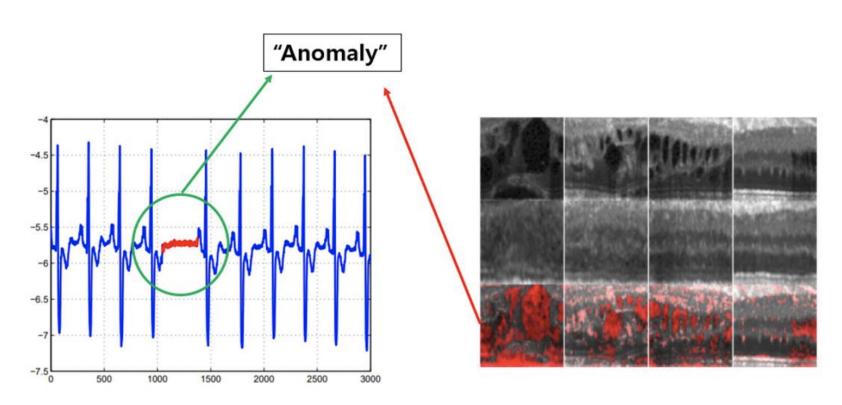


HOW WE CAN DO? Communication!! Al is just a Tool, but Al is a good Tool !!



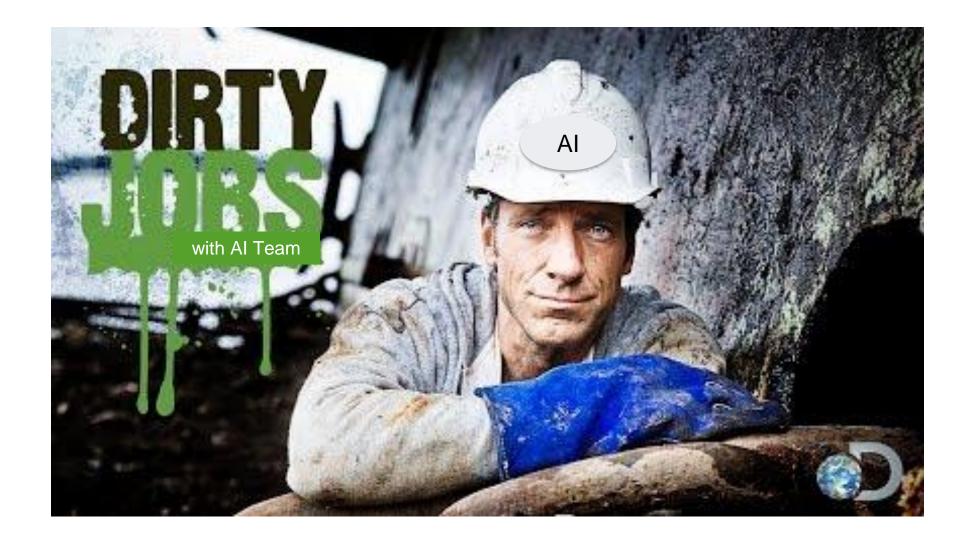
HOW WE CAN DO? Communication!! Al is just a Tool, but Al is a good Tool !!

Normality = Majority ? Normality != Majority !



Reference [1] Anomaly Detection of Time Series, 2010 [2] Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery, 2017

HOW WE CAN DO? Dirty Job First!!



HOW WE CAN DO? We are a STARTUP!!



THIS DOES NOT MEAN WE ARE COMPETING WITH GOOGLE, FACEBOOK, NAVER, KAKAO, ...

THANK YOU FOR UNDERSTANDING

2,4,8 weeks process

2 weeks → feasibility check 4 weeks → first POC 8 weeks → Paper POC Otherwise... Give up and wait for Google to do it!! Focus on impact and speed!! For not fancy AI, but For domain & user!!

HOW WE CAN DO? We do not make AI, but make use of AI!!

Domain Good data, insight, ...

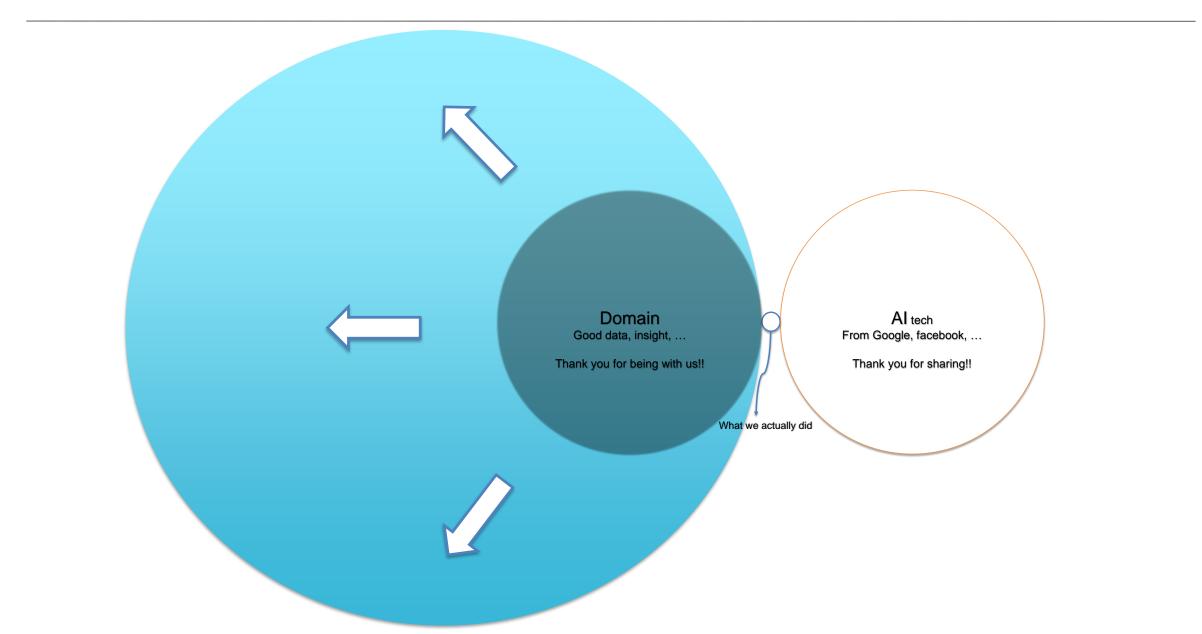
Thank you for being with us!!

AI tech From Google, facebook, ...

Thank you for sharing!!

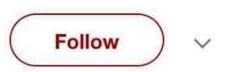
What we actually did

WHAT WE WANT?



WHAT WE KNOW ?





Editor of @JAMA_current @howardbauchner at @StanfordDeptMed Grand Rounds "We are no longer accepting papers that show machines are as good as humans at looking at medical images, we know that." We are now seeking work showing clinical impact of AI.

1:25 AM - 7 Feb 2019

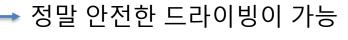
WHAT WE KNOW ?







정말 상용화된다고 하면





WHAT WE KNOW ?

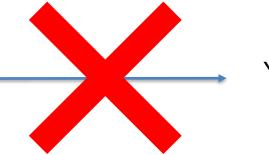


정말 안전한 드라이빙이 가능하면



정말 상용화될 수 있다.

We have Clinical papers, Patents, Fancy Al papers,



You can use ...





고맙습니다!