
BMES 2017
BMES
BIOMEDICAL ENGINEERING SOCIETY™
2017 BMES Annual Meeting
October 11–14, 2017
Phoenix Convention Center
Phoenix, Arizona
Shelly Sakiyama-Elbert
Meeting Co-Chair
University of Texas at Austin
Kevin Otto
Meeting Co-Chair
University of Florida
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3:30 pm
Real-Time Label-Free Imaging of Dynamic Metabolic Processes During Apoptosis In Live Cells
Marina Marjanovic[1], Andrew Bower[1], Joanne Li[1], Eric Chaney[1], and Stephen Boppart[1]
[1]*University of Illinois at Urbana-Champaign, Urbana, IL*

3:45 pm
Improved Performance in Fiber Bundle Imaging Systems Via Dithering
Arthur Gmitro[1], Andrew Rouse[1], and Neil Momsen[1]
[1]*University of Arizona, Tucson, AZ*

4:00 pm
Photonic Inactivation of Virus Particles by Femtosecond Lasers
Mina Nazari[1], Rahm Gummuluru[1], Mi Hong[1], Björn Reinhard[1], and Shyamsunder Erramilli[1]
[1]*Boston University, Boston, MA*

4:15 pm
Noncontact 3-dimensional Speckle Contrast Diffuse Correlation Tomography of Tissue Blood Flow Distribution
Mingjun Zhao[1], Chong Huang[1], Daniel Irwin[1], Siavash Mazdeyasna[1], Nneamaka Agochukwu[1], Ruohui Li[1,2], Lesley Wong[1], and Guoqiang Yu[1]
[1]*University of Kentucky, Lexington, KY,* [2]*Beijing Union University, Beijing, China, People's Republic of*

4:30 Pm
Accurate Segmentation of Pressure Ulcer Images
Ahmed Shalaby[1], Ali Mahmoud[1], Begoña García-Zapirain[2], Adel Elmaghraby[1], and Ayman El-Baz[1]
[1]*University of Louisville, Louisville, KY,* [2]*EVIDA Research Group,Deusto University, Spain, Deusto, Spain*

OP-Sat-3-9 — Room 228A

Track: Device Technologies and Biomedical Robotics

Affordable Health and Frugal Innovation

Chairs: Adam Brown, Perry Weinthal

3:15 pm
Automating Biomarker Concentration and Signal Enhancement for Paper-Based Chlamydia Detection
Daniel Bradbury[1], April Pan[1], Benjamin Wu[1,2], and Daniel Kamei[1]
[1]*University of California Los Angeles, Los Angeles, CA,* [2]*School of Dentistry, University of California Los Angeles, Los Angeles, CA*

3:30 pm
Measuring the Mass, Volume, and Density of Microgram-Sized Objects in Fluids
Shirin Mesbah Oskui[1], Heran Bhakta[1], Graciel Diamante[1], Huinan Liu[1], Daniel Schlenk[1], and William Grover[1]
[1]*University of California, Riverside, Riverside, CA*

3:45 pm
Implementation of a Split Trehalase in an Electrochemical Biosensor for Rapid Point-of-Care Detection of Antibodies and Biomarkers of Disease
Jeroen De Buck[1] and Marija Drikic[1]
[1]*University of Calgary, Calgary, AB, Canada*

4:00 pm
Rapid Workflow for Cancer Cell Genomics
Adam Snider[1] and Anubhav Tripathi[1]
[1]*Brown University, Providence, RI*

4:15 pm
Open-Source Device for Variable Ulnar Eminence
Perry Weinthal[1]
[1]*Florida Atlantic University, Boca Raton, FL*

4:30 pm
Point-of-Care System for Monitoring Cellular Adhesion in Sickle Cell Disease
Mark Lewandowski[1], Jonathon Koss[1], Jane Little[1], and Umut Gurkan[1]
[1]*Case Western Reserve University, Cleveland, OH*

OP-Sat-3-10 — Room 226A

Track: Bioinformatics, Computational and Systems Biology

Analysis of Cell Signaling

Chairs: Megan McClean, Princess Imoukhuede

3:15 pm
A Rule-based Model of the CamKII Holoenzyme
Matthew Pharris[1], Melanie Stefan[2], and Tamara Kinzer-Ursem[1]
[1]*Purdue University, West Lafayette, IN,* [2]*The University of Edinburgh, Edinburgh, United Kingdom*

3:30 pm
How Specific Sequence Features of FG Nups Affect Nucleocytoplasmic Transport
Mohaddeseh Peyro[1], Mohammad Soheilypour[1], Ali Ghavami[1], Briana Lee[1], and Mohammad Mofrad[1]
[1]*University of California Berkeley, Berkeley, CA*

3:45 pm
Keratinocyte ERK Signaling is Modulated by Growth Factor Presentation Scheme and Cellular Tight Junctions
Pamela Kreeger[1], Chloe Kim[1], Sarah Jacobsen[1], Cameron Stewart[1], Megan McClean[1], and Kristyn Masters[1]
[1]*University of Wisconsin-Madison, Madison, WI*

4:00 pm
Computational Model Predicts the Dynamics of Thrombospondin-1 Mediated Apoptosis Signaling
Qianhui Wu[1], Jennifer Rohrs[1], Pin Wang[1], and Stacey Finley[1]
[1]*University of Southern California, Los Angeles, CA*

Saturday, October 14 | 3:15 pm–4:45 pm | Platform Session 3

4:15 pm
Large-scale Logic-based Differential Equation Computational Model Revealed a New Dimension in Macrophage Polarization
Xiaji Liu[1], Jingyuan Zhang[1], Angela Zeigler[1], Merry Lindsey[2,3], and Jeffrey Saucerman[1]
[1]*University of Virginia, Charlottesville, VA,* [2]*University of Mississippi Medical Center, Jackson, MS,* [3]*G.V. (Sonny) Montgomery Veterans Affairs Medical Center, Jackson, MS*

4:30 pm
High-dimensional Single-cell Signaling Analysis Identifies Novel Targets for Eradicating Latent HIV-infected T Cells
Linda Fong[1] and Kathryn Miller-Jensen[1]
[1]*Yale University, New Haven, CT*

OP-Sat-3-11 — Room 226B

Track: Neural Engineering

CNS Repair and Regeneration

Chairs: Stephanie Seidlits, Ryan Koppes

3:15 pm
Improving Functional Gains in a Skilled Reaching Task Following Brain Injury Through Combinatorial Neural Stem Cell and Motor Rehabilitation Therapy
Caroline Addington[1], Gergey Mousa[2], Peter Hillebrand[2], Amber Bengson[2], Kristen Okada[2], Akshara Thakore[2], Sarah Stabenfeldt[2], and Jeffrey Kleim[2]
[1]*University of Virginia, Charlottesville, VA,* [2]*Arizona State University, Tempe, AZ*

3:30 pm
Endogenous Neural Stem Cell Activation After Traumatic Brain Injury
Jeremy Anderson[1], Misaal Patel[1], Quinn Wade[1], Kelvin Kwan[1], and Li Cai[1]
[1]*Rutgers University, Piscataway, NJ*

3:45 pm
Feasibility of Nanoparticle Delivery Correlates With Blood Brain Barrier Permeability After Diffuse Brain Injury
Vimala Bharadwaj[1], Rachel Rowe[2], Jordan Harrison[2], Chen Wu[2], Trent Anderson[2], Jonathan Lifshitz[2,3], P. David Adelson[3], Vikram Kodibagkar[1], and Sarah Stabenfeldt[1]
[1]*Arizona State University, Tempe, AZ,* [2]*University of Arizona, College of Medicine-Phoenix, Phoenix, AZ,* [3]*Barrow Neurological Institute at Phoenix Children's Hospital, Phoenix, AZ*

4:00 pm
Implantation of an Astrocyte Extracelllular Matrix Containing Hydrogel Improves Neural Fiber Growth into a Spinal Cord Lesion
Russell Thompson[1,2], Jennifer Pardieck[1,2], Lindsey Crawford[2], and Shelly Sakiyama-Elbert[1]
[1]*University of Texas-Austin, Austin, TX,* [2]*Washington University in St Louis, St Louis, MO*

4:15 pm
IL-4-Releasing Films Shift Macrophages to an Anti-inflammatory State for Spinal Cord Injury Regeneration
Alexis Ziemba[1], Anthony D'Amato[1], Devan Puhl[1], Taylor MacEwen[1], Abigail Koppes[2], Ryan Gilbert[1], Michelle Lennartz[3], and Ryan Koppes[2]
[1]*Rensselaer Polytechnic Institute, Troy, NY,* [2]*Northeastern University, Boston, MA,* [3]*Albany Medical Center, Albany, NY*

4:30 pm
Combinatorial Lentiviral Gene Delivery of Pro-oligodendrogenic Factors to Improve Myelination of Regenerating Axons After Spinal Cord Injury
Dominique Smith[1], Daniel Margul[2], Mitchell Johnson[1], and Lonnie Shea[1]
[1]*University of Michigan - Ann Arbor, Ann Arbor, MI,* [2]*Northwestern University, Chicago, IL*

OP-Sat-3-12 — Room 227C

Track: Undergraduate Research, Design & Leadership

Undergraduate Research, Design & Leadership III

Chairs: Jeffrey La Belle, Tim Becker

3:15 pm
The Influences of Mitochondrial Depolarization on Mitochondrial Network Structures
Shao-Ting Chiu[1], Jun-Yi Leu[2], and An-Chi Wei[1]
[1]*Department of Electrical Engineering, National Taiwan University, Taipei, Taiwan,* [2]*Institute of Molecular Biology, Academia Sinica, Taipei, Taiwan*

3:24 pm
3-Dimensional Fluid-Structure Interaction Computational Model of Heart Valves for Bioreactor Optimization
Frederic Blais[1], Giulia Luraghi[2], Francesco Migliavacca[2], Giancarlo Pennati[2], Leslie Sierad[1,3], and Ethan Kung[1]
[1]*Clemson University, Clemson, SC,* [2]*Politecnico di Milano, Milan, Italy,* [3]*Aptus Bioreactors, Clemson, SC*

3:33 pm
Antibacterial Effects of Copper-PDMS Membranes for Artificial Lungs
Angela Lai[1], Neha Kapate[1], Neil Carleton[1], and Keith Cook[1]
[1]*Carnegie Mellon University, Pittsburgh, PA*

3:42 pm
Similarity in Viral and Host Promoters Couples Viral Reactivation with Host Cell Migration
Kathrin Bohn-Wippert[1], Erin Tevonian[1], Melina Megaridis[1], and Roy Dar[1]
[1]*University of Illinois at Urbana-Champagin, Urbana, IL*

The Influences of Mitochondrial Depolarization on Mitochondrial Network Structures

Shao-Ting Chiu[1], Jun-Yi Leu[2], and An-Chi Wei[1]
[1]Department of Electrical Engineering, National Taiwan University, Taipei, Taiwan,
[2]Institute of Molecular Biology, Academia Sinica, Taipei, Taiwan

Introduction: The mitochondrial life cycle includes fission and fusion, which contribute to the dynamic morphology. Besides, mounting evidence indicates that mitochondrial fusion process avoids damaged mitochondria from fusing with others based on mitochondrial membrane potential. However, how mitochondrial damage influences mitochondrial network remains unclear. In this study, we first depolarized mitochondria by uncoupler, and investigated changes of mitochondrial 3D structure from a network point of view. Also, we have implemented an artificial neural network for automatic recognition of damaged mitochondrial network. This study provides insights into morphological response to mitochondrial damage and possible application to clinical diagnosis.

Materials and Methods: *S. cerevisiae* S288C labeled with Kgd1-GFP was used for mitochondrial imaging. Cells were treated with 10 μM FCCP (carbonylcyanide-p-trifluorometoxyphenylhydrazon), a mitochondrial uncoupler, for 50 min to depolarize mitochondria, and the untreated cells are regarded as the control. Mitochondrial 3D images were captured by a Delta Vision microscope, and processed by MitoGraph software (Fig. 1A). We further calculated network features including network density (the ratio of actual connections to potential connections), average and variance of mitochondrial length, network size (number of nodes). The comparison for two groups was calculated by Mann-Whitney U test. Moreover, we have constructed a full-connected neural network with two hidden layers to classify mitochondrial morphology into two groups.

Results and Discussion: Network density, average and variance of mitochondrial length decrease significantly after FCCP treatment (Fig. 1B), while the network size increases significantly compared to the untreated population. The slower fusion rate of damaged mitochondria may contribute to increased nodes and decreased connections in the mitochondrial network, which result in lower network density and higher size. The fragmentation may also result in lower average and variance of mitochondrial length in the damaged network. The implemented neural network performs at 68% accuracy (Fig. 1C), applying deep learning framework may improve the performance.

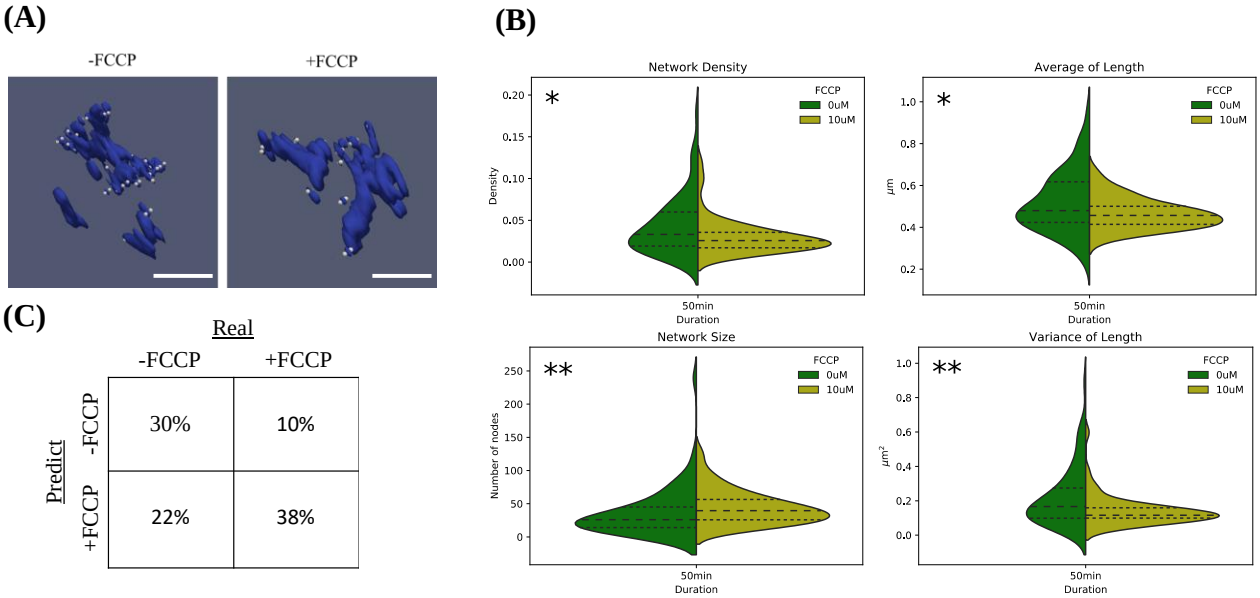


Fig. 1. (A) Mitochondrial morphology with or without FCCP treatment (10 μM). Blue part represents the mitochondrial surface, and white part represents the mitochondrial skeleton. Scale bars represent 2 μm (B) The effect of FCCP treatment to the mitochondrial network (n=126). *P < 0.05 and **P < 0.01 vs. control (Mann-Whitney U test, one-tailed) (C) Classification results. A neural network was used to classify mitochondrial status based on four mitochondrial network features (n=126).

Conclusions: The morphological changes caused by mitochondrial uncoupler includes lower density, average and variance of mitochondrial length, and higher network size. The significantly different features provide opportunities for automatic recognition of damaged mitochondrial morphology.

The Influences of Mitochondrial Depolarization on Mitochondrial Network Structures

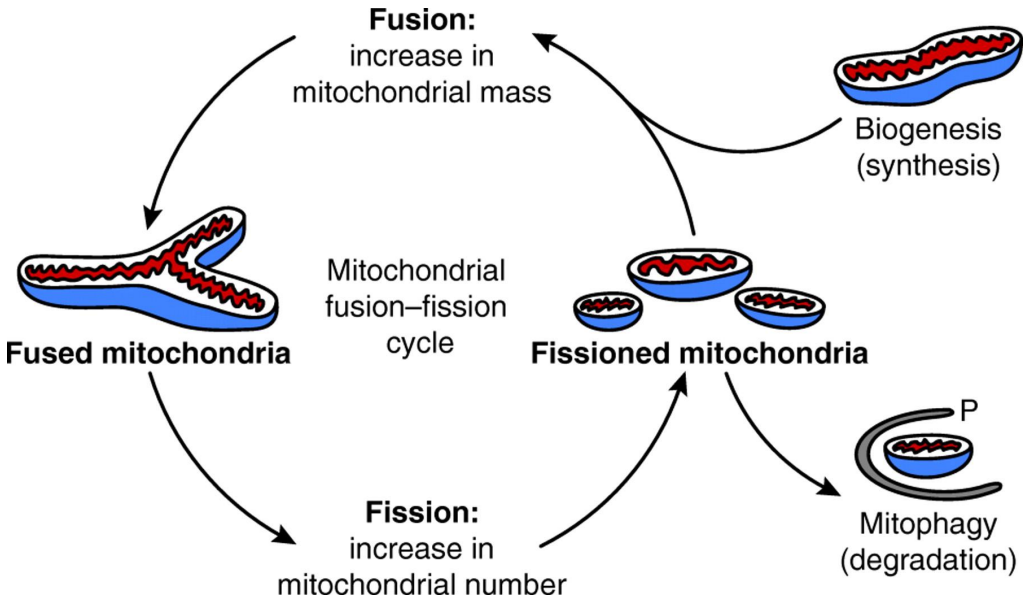
Shao-Ting Chiu

Department of Electrical Engineering,
National Taiwan University, Taipei, Taiwan

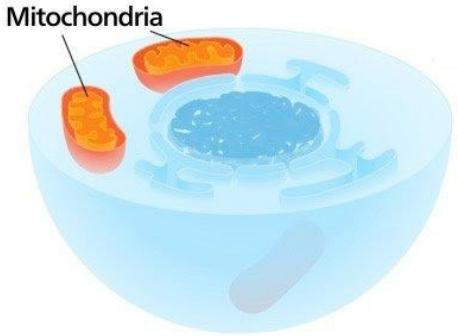
BMES 2017, Phoenix

Introduction

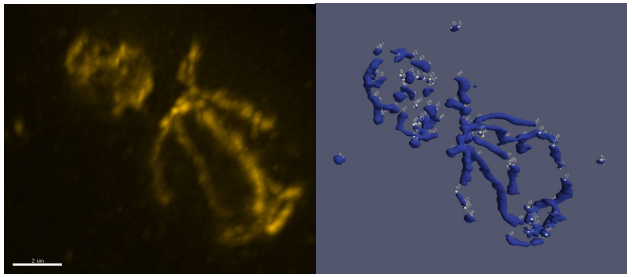
(2) Mitochondrial life cycle



(1) Mitochondria in a cell



(3) Yeast mitochondrial network



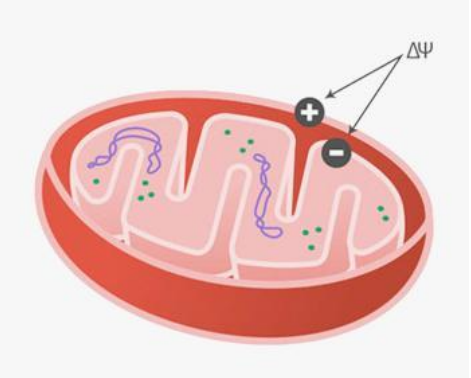
(Left) 3D mitochondrial structure
(Right) Skeletonized mitochondrial network

Figure (1), (2) from Arnold Y. S. et al. J. Cell Sci. (2010)

Main Questions

- What are the differences between normal and depolarized mitochondrial network?
  - Graph theory provides useful features to distinguish mitochondrial morphology

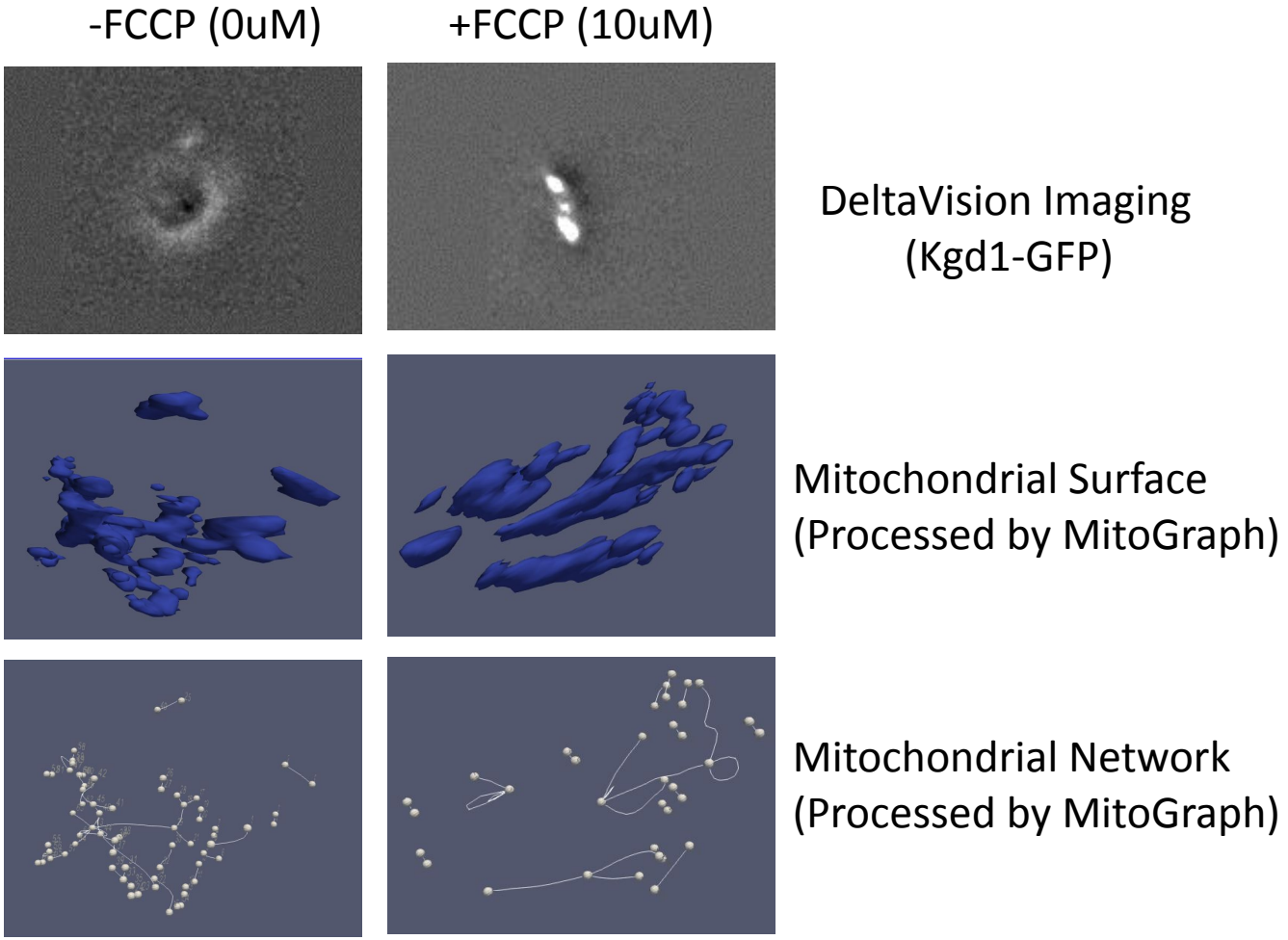
- How to predict depolarization based on mitochondrial morphology?



Mitochondrial membrane potential

Figure from ThermoFisher Website

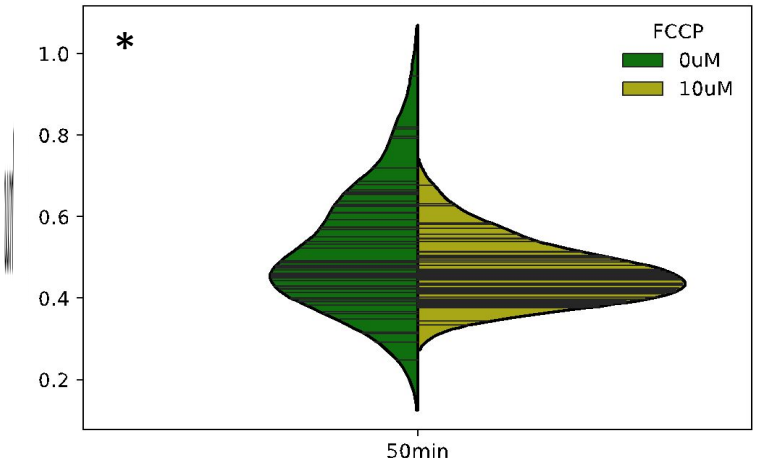
Yeast Mitochondrial 3D Imaging and Depolarization



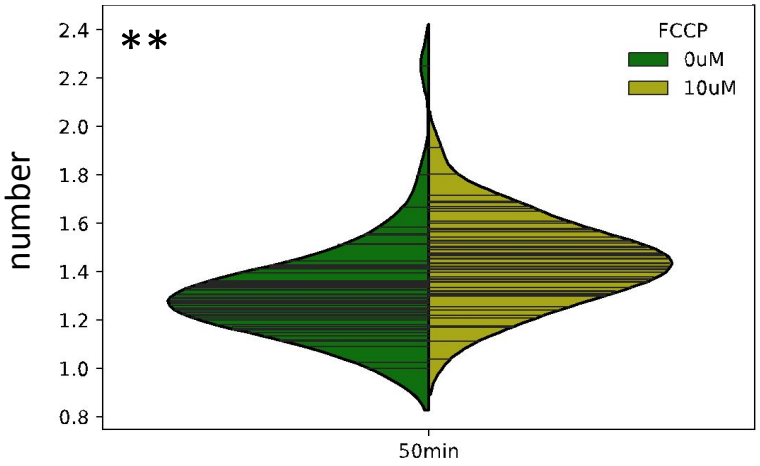
+FCCP: 10uM FCCP (uncoupler), 50 min treatment. MitoGraph software: Viana et al. Biophys. Method (2015)

Network Properties (1)

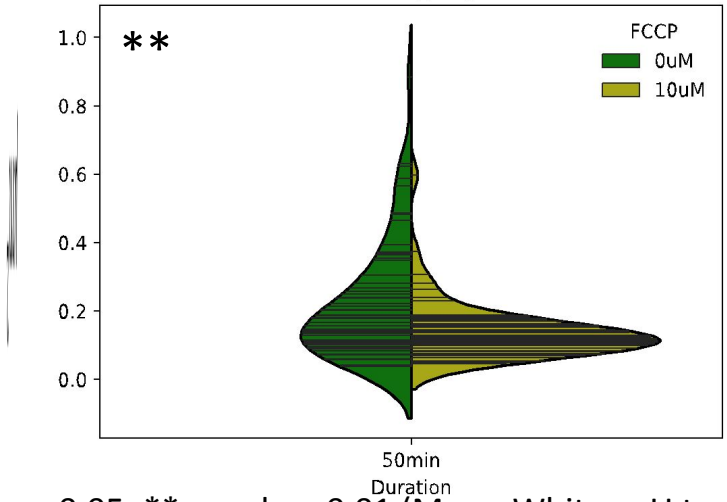
Average of Length



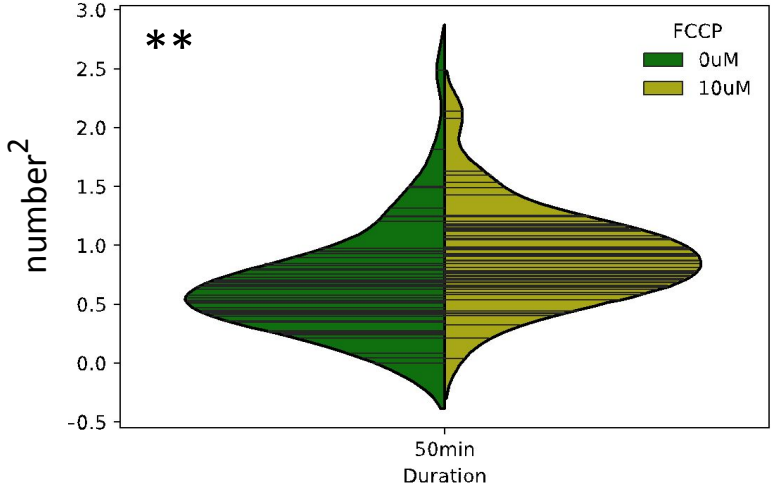
Average of Degree



Variance of Length



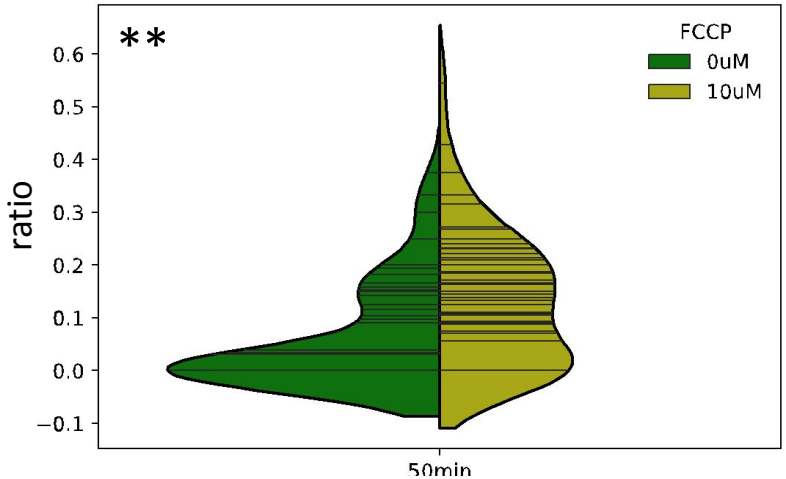
Variance of Degree



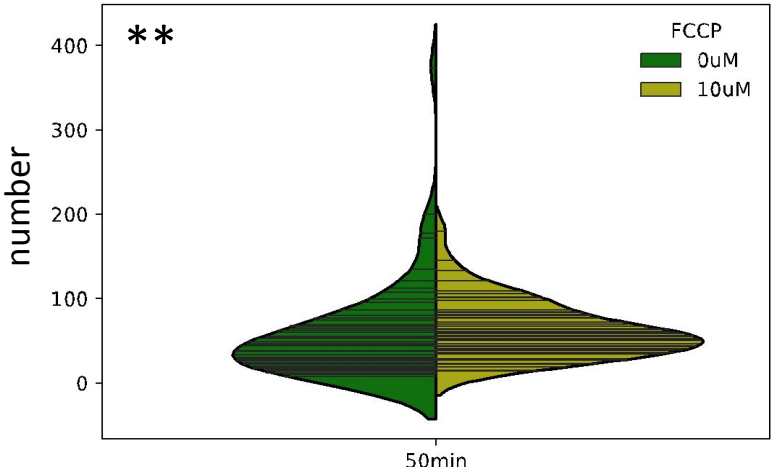
*: p value<0.05; **: p value<0.01 (Mann-Whitney U test, two-tailed)

Network Properties (2)

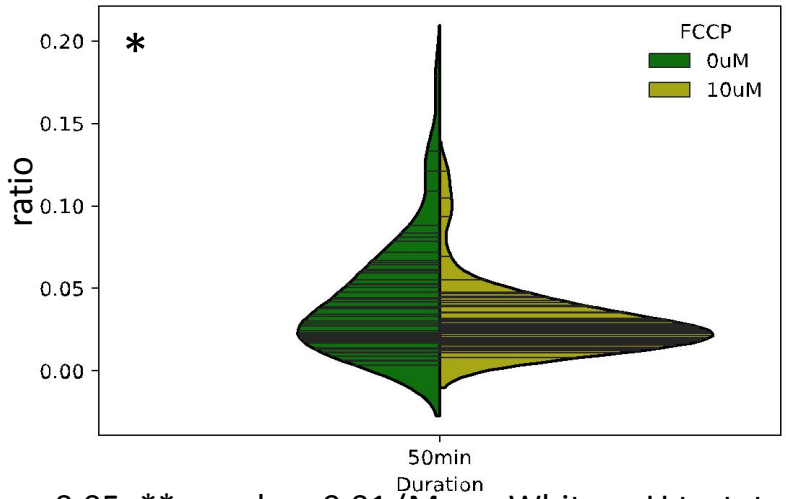
Transitivity



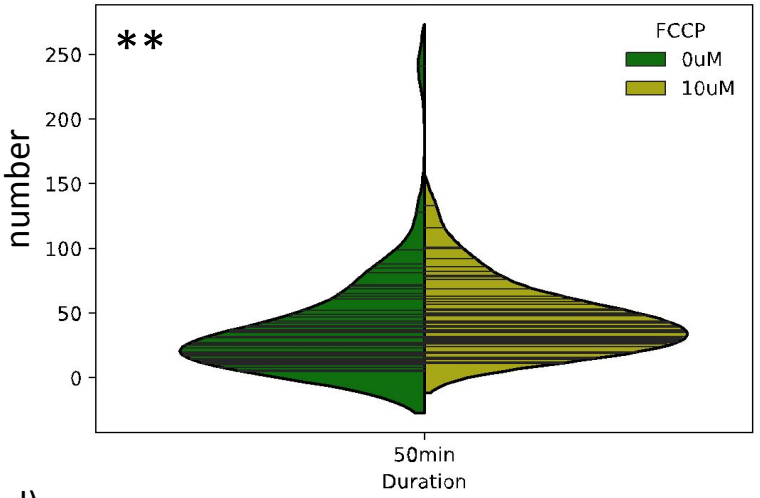
Number of Nodes



Density



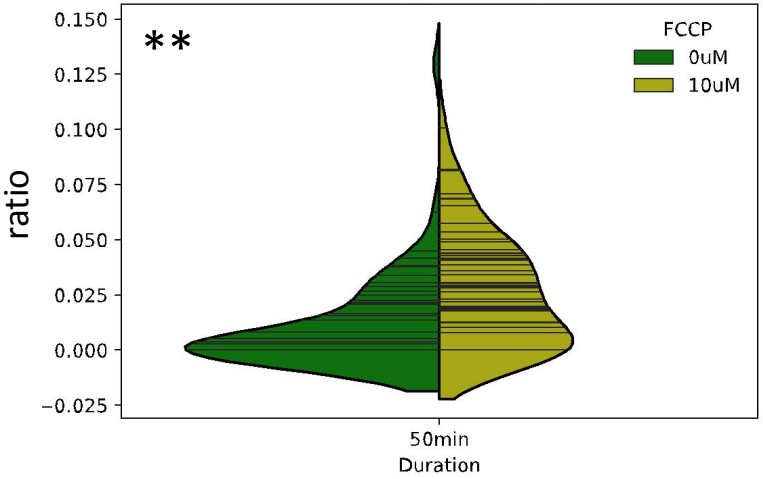
Number of Edges



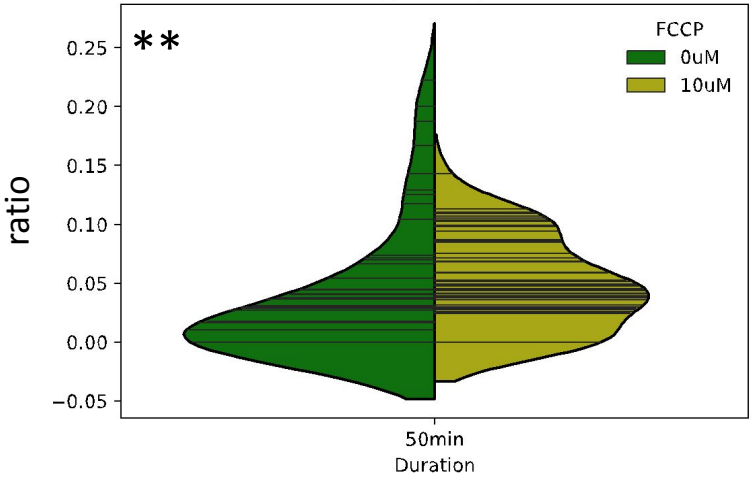
*: p value<0.05; **: p value<0.01 (Mann-Whitney U test, two-tailed)

Network Properties (3)

Average of clustering coefficient

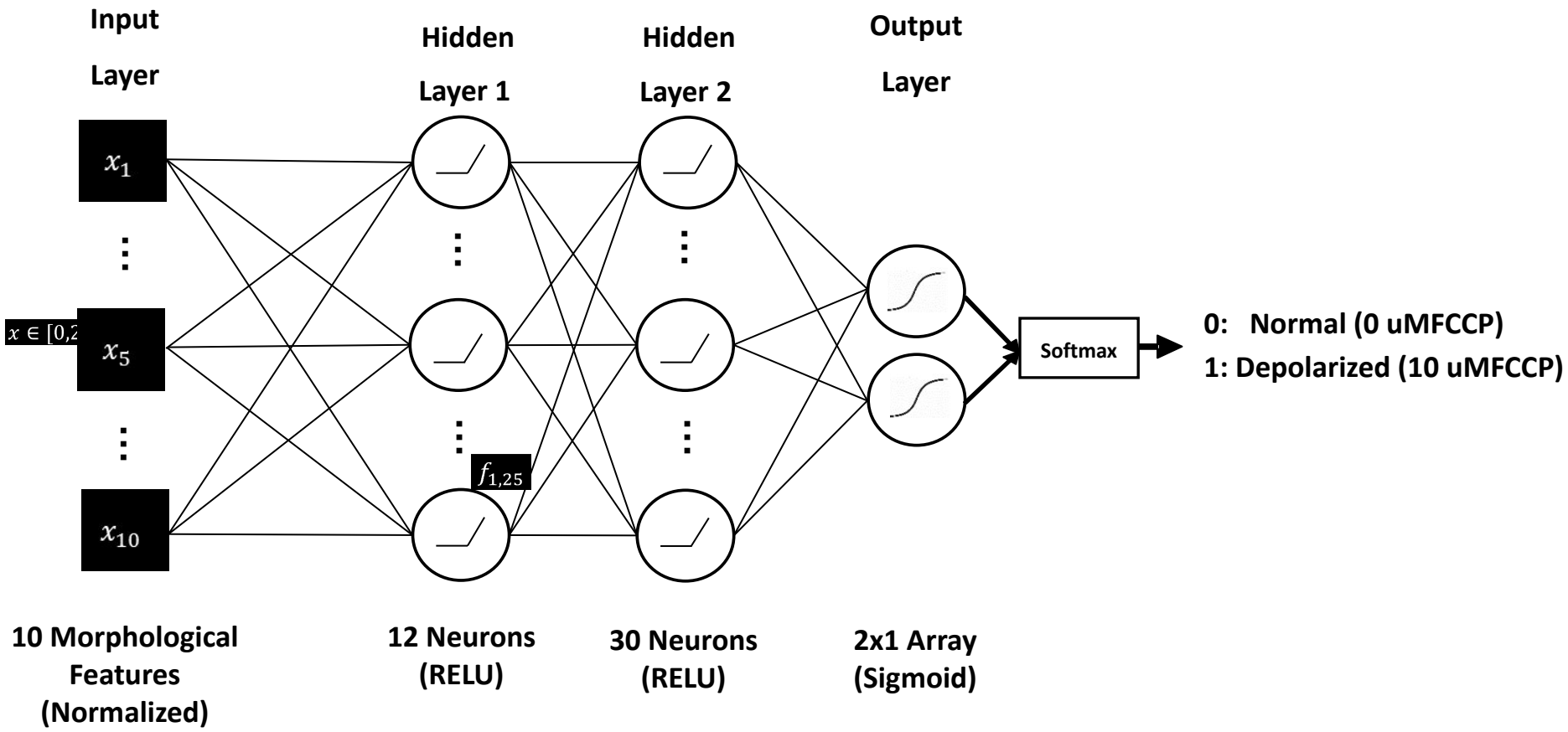


Number of multi-connected Nodes



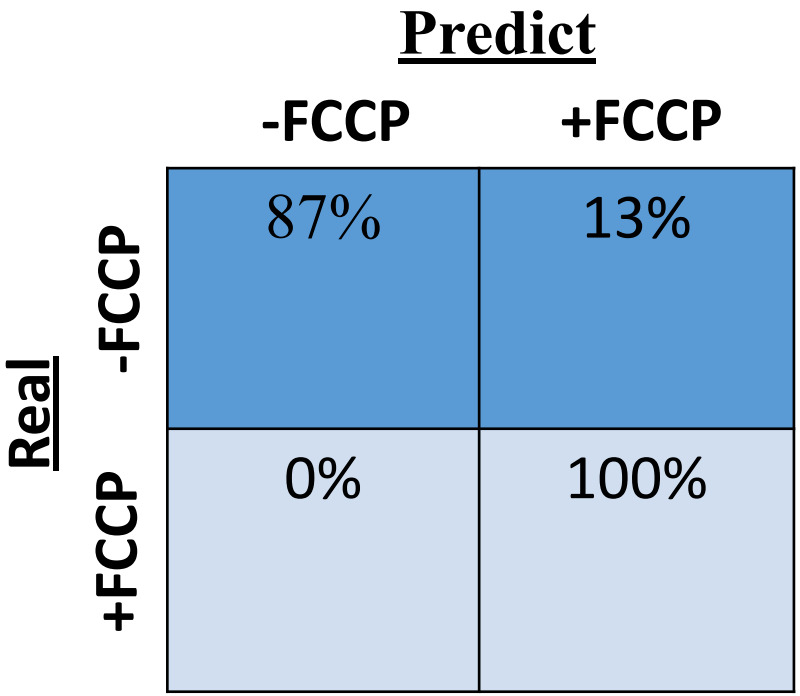
*: p value<0.05; **: p value<0.01 (Mann-Whitney U test, two-tailed)

Artificial Neural Network for Mitochondrial Depolarization Detection



Performance of Classification

- Testing accuracy: 90% (62 samples)



- Training accuracy: 100% (63 samples)

Discussion

- Depolarized mitochondrial network possesses lower average and variance of length can be explained by decreased mitochondrial fusion rate.

- Though the differences of network features between normal and depolarized mitochondria are little, the combination of these features is still enough to predict the conditions.

- The main source of prediction error is from false positive (type I error).

Summary

- Normal and depolarized mitochondrial network possessed at least 10 network features in significant difference.

- Implemented Artificial neural network can predict mitochondrial depolarization based on morphological features in 90% accuracy.

Acknowledgement

- Supervisors

 Dr. An-Chi Wei

Department of Electrical Engineering,
National Taiwan University

 Dr. Jun-Yi Leu

Institute of Molecular Biology,
Academia Sinica, Taipei, Taiwan

- EE Student travel fund

- Supported by

Supplemental Materials

G: network; V: a node; k_v: degree of V;

N_V: Number of links between neighbors of V

- Clustering Coefficient (C(V))

$$C(V) = \frac{N_V}{C_2^{k_v}}$$

- Density(D(G))

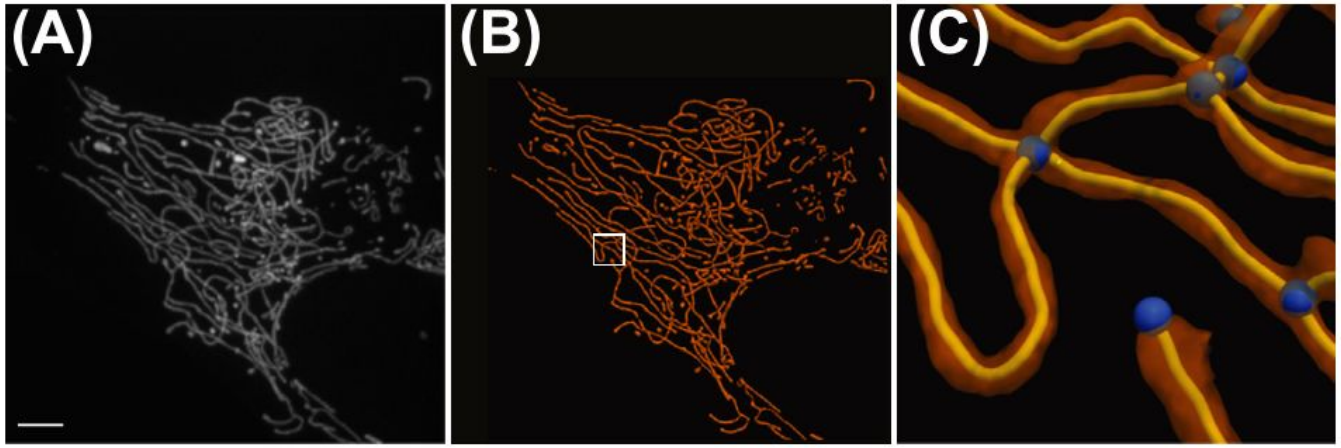
$$D(G) = \frac{Number\ of\ edges\ in\ G}{C_2^{Number\ of\ nodes\ in\ G}}$$

- Transitivity(T(G))

$$T(G) \quad 3 \times Triangles$$

Supplemental Materials

- Human bone osteosarcoma possesses sophisticated mitochondrial network



Confocal image | **Mitochondrial surface** | **Mitochondrial network**

Figures from M. P. Viana et al. (2015)