extract more accurate values of dry mass NOTE: • If you're using google colaboratory to run this notebook, please uncomment the code in the following cell to clone the repository. • If you're running the notebook on your local machine, please skip this step to avoid cloing the repository in the current folder. # !git clone https://github.com/softmatterlab/Quantitative-Microplankton-Tracker.git In [1]: # %cd Quantitative-Microplankton-Tracker/examples/ In [2]: %matplotlib inline import sys sys.path.append("..") 1. Setup Import the dependencies to run this tutorial. In [3]: import glob import numpy as np import tensorflow as tf import matplotlib.pyplot as plt import deeptrack as dt 2. Load experimental holographic image Experimental images are located in sample-data folder In [4]: # Load figure 3 data (feeding events) predator sequence = np.load("../data/data_figure3/predator_sequence.npy" prey sequence = np.load("../data/data figure3/prey_sequence.npy" # Load figure 4 data (division events) cell1 sequence = np.load("../data/data figure4/Cell1 sequence.npy" cell2_sequence = np.load("../data/data figure4/Cell2 sequence.npy" cell3 sequence = np.load("../data/data figure4/Cell3 sequence.npy" 2.1. Visualize prey and predator planktons In [5]: plt.figure(figsize=(10, 5)) plt.subplot(1,2,1)plt.title("Predator hologram (\$\it{Oxyrrhis\ Marina}\$)") plt.imshow(predator_sequence[0], cmap="gray") plt.subplot(1,2,2)plt.title("Prey hologram (\$\it{Dunaliella\ tertiolecta}\$)") plt.imshow(prey_sequence[0], cmap="gray") Out[5]: <matplotlib.image.AxesImage at 0x7fa5a68ef6a0> Predator hologram (Oxyrrhis Marina) Prey hologram (Dunaliella tertiolecta) 10 10 20 20 30 40 50 3. Load pre-trained WAC-Net model We define the WAC-Net model and load the weights from a pre-trained model. In [6]: # WAC-Net trained for feeding events feeding model = dt.models.WACNet(outputs = 2) # 2 outputs: dry mass and radius feeding model.load weights("../pre-trained-models/WACNet dry mass.h5" # WAC-Net models trained for division events division_event_models_loc = glob.glob("../pre-trained-models/division-event-models/*.h5" division models = []for model loc in division event models loc: empty model = dt.models.WACNet(outputs = 1) empty model.load weights(model loc) division_models.append(empty_model) 4. WAC-Net prediction on experimental sequences 4.1. Example 1 - Feeding events Feeding events are recorded in two sequences: • predator sequence contains predator frames • prey sequence contains prey frames 4.1.1. Normalise the experimental image Normalise and reshape the image for WAC-Net prediction In [7]: def Normalise(images, batch = 15): Normalised = []for i in range(len(images)): Normalised.append(images[i]/np.median(images[i])) Normalised = np.array(Normalised)-1 proc = [] #sliding window for i in range(len(Normalised)-batch+1): proc.append(Normalised[i:i+batch]) return np.expand dims(proc, axis = -1) In [8]: | # Funtion to convert the predicted dry mass to real dry mass units (pico grams) def real_dm(p, a=209.16, b=0.28, sp_ri_inc = 0.21): return (p*a+b)/sp_ri_inc 4.1.2. Prediction on experimental sequences Experimental sequences are normalized with batch size of 1. batch value can be increased to generate a sliding window of the experimental sequence. The WAC-Net assigns weights to the images with in sliding windows to predict the best possible value for dry mass considering all the frames. In [9]: | prediction_predator = feeding_model.predict(Normalise(predator sequence, batch = 1) prediction_prey = feeding_model.predict(Normalise(prey sequence, batch = 14.1.3. Convert values to real dry mass units In [10]: drymass predator = real dm(prediction predator[:,0]) drymass prey = real dm(prediction prey[:,0]) 4.4. Visualise the dry mass transition in a feeding event In [11]: feeding at = 219 fig, ax = plt.subplots(figsize=(15, 5)) plt.title("Feeding event") plt.plot(np.arange(0, feeding at, 1), drymass predator[0:feeding at], linestyle='dashed',color='orange', marker='.', label='\$\it{Oxyrrhis\ Marina}\$ pre-feeding', alpha = 1, markersize = '5') plt.plot(np.arange(feeding_at,len(drymass_predator), 1),drymass_predator[feeding_at:], linestyle='dashe d',color='darkorange', marker='.', label='\$\it{Oxyrrhis\ Marina}\$ post-feeding', alpha = 1, markersize plt.plot(drymass_prey[:feeding_at], linestyle='dashed',color='blue', marker='.', label='\$\it{Dunaliella \ Teriolecta}\$', alpha=1, markersize = '5') plt.xlabel('Time (seconds)') plt.ylabel('Drymass (in picograms)') xticks = np.arange(0,550,50)ax.set xticks(xticks) ax.set_xticklabels([int(x*(1/10)) for x in xticks]) plt.legend(prop={'size': 16}) plt.show() Feeding event 700 Oxyrrhis Marina pre-feeding 600 Oxyrrhis Marina post-feeding Dunaliella Teriolecta 500 Drymass (in picograms) 400 300 200 100 0 15 20 Time (seconds) 4.2. Example 2 - Double division event Division events are recorded in three sequences: • cell1_sequence contains frames of parent cell, Gen 1 daughter cell 1, and Gen 2 daughter cell 1 • cell2_sequence contains frames of Gen 1 daughter cell 2 (along with parent cell) • cell3_sequence contains frames of Gen 2 daughter cell 2 (along with parent cell and Gen 1 daugher cell 1) 4.2.1. Normalise and predict Function to de-normalise the dry mass values In [12]: def dm range(rad range, ri range): m = lambda rad, ri: ((4*np.pi)/3) * ((rad*1e+6)**3) * (ri-1.33)return m(rad_range[0], ri_range[0]), m(rad_range[1], ri_range[1]) $dm_vals = dm_range([4e-6, 9e-6], [1.35, 1.38])$ dm vals Out[12]: (5.361651462126584, 152.6814029644634) Predictions on cell 1 sequence In [13]: _dm_cell1=[] for i in range(len(division_models)): pred = division_models[i].predict(Normalise(cell1 sequence, batch = 15)[:,0]

Example 2. Using WAC-Net

Open in Colab

This example demonstrates how to use a pre-trained WAC-Net (Weighted average convolutional neural network) on experimental images to

pred = real_dm(pred, dm_vals[1]-dm_vals[0], dm_vals[0])

pred = real dm(pred, dm vals[1]-dm vals[0], dm vals[0])

pred = real_dm(pred, dm_vals[1]-dm_vals[0], dm_vals[0])

_dm_cell1.append(pred)

Predictions on cell 2 sequence

Normalise(

_dm_cell2.append(pred)

Predictions on cell 3 sequence

Normalise(

_dm_cell3.append(pred)

dm cell3=[]

)[:,0]

dm cell2=[]

))[:,0]

In [14]:

In [15]:

dm cell1 = np.mean(dm cell1, axis=0)

for i in range(len(division models)):

cell2_sequence,

dm_cell2 = np.mean(_dm_cell2, axis=0)

for i in range(len(division_models)):

cell3_sequence,

dm_cell3 = np.mean(_dm_cell3, axis=0)

4.2.2. Visualise the dry mass dynamics in a double division event

pred = division_models[i].predict(

pred = division_models[i].predict(

marker='.', label='Generation 1 - Daughter Cell 2', alpha=1, markersize='10', linewidth=3) #d isplaced cell # Second generation---plt.plot(time[dt2:end1], dm_cell1[dt2:end1], linestyle='dashed', color="darkcyan", marker='.', label='\nGeneration 2 - Daughter cell 1', alpha=1, markersize='10', linewidth=3) # stationary cell plt.plot(time[dt2:end1], dm_cell3[dt2:end1], linestyle='dashed', color="darkcyan", marker='.', label='Generation 2 - Daughter cell 2', alpha=1, markersize='10', linewidth=3) # daughtercell1 **def** place_ticks(x = 10, y = 10): plt.locator_params(axis="x", nbins=x) plt.locator_params(axis="y", nbins=y) xticks = np.arange(0,700,14.5)ax.set_xticks(xticks) ax.set_xticklabels([np.round(x*(5/6/60),1) for x in xticks]) place_ticks(x=10, y=10) fs = 30plt.xticks(fontsize=fs) plt.yticks(fontsize=fs) plt.legend(prop={'size': fs}) plt.ylabel("Dry mass (pg)", fontsize=fs) plt.xlabel("Time (hours)", fontsize=fs) plt.ylim([0, 700]) plt.show() 700_T ---- Parent Cell Generation 1 - Daughter Cell 1 600 ---- Generation 1 - Daughter Cell 2 500 Generation 2 - Daughter cell 1 Ory mass (pg) ---- Generation 2 - Daughter cell 2 200 100 4.0 Time (hours)

In [16]: | time = np.arange(0, len(dm_cell1), 1)

dt1 = 128 dt2 = 335end1 = 600

 $daughter_lim = 10$

stationary cell

fig,ax = plt.subplots(figsize=(40, 14))

plt.plot(time[10:dt1], dm_cell1[10:dt1], linestyle='dashed', color="midnightblue",

plt.plot(time[dt1:dt2], dm_cell1[dt1:dt2], linestyle='dashed', color="orange",

marker='.', label='Parent Cell', alpha=1, markersize=10, linewidth=3) # parentcell1

plt.plot(time[dt1:dt2-daughter lim], dm cell2[dt1:dt2-daughter lim], linestyle='dashed', color="orange"

marker='.', label='\nGeneration 1 - Daughter Cell 1', alpha=1, markersize='10', linewidth=3) #