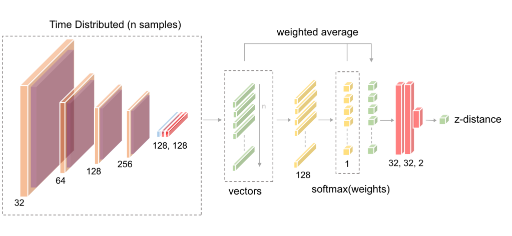
Tutorial 3. Training WAC-Net to predict plankton vertical positions

Open in Colab

This tutorial demonstrates how to train a WAC-Net (Weighted average convolutional neural network) for refining the predicted properties from RU-Net. It covers information on:

- Defininig Simulation parameters
- Defining WAC-Net model using tensorflow keras
- Training WAC-Net model
- Testing the model on an experimental images



NOTE:

- If you're running this notebook on your local machine, please comment the code in the cell below

In [8]:
```
!git clone https://github.com/softmatterlab/Quantitative-Microplankton-Tracker.git
%cd Quantitative-Microplankton-Tracker/training-tutorials/
```

In [9]:
```
%matplotlib inline
import sys
sys.path.append("..")
```

1. Setup

Imports the dependencies needed to run this tutorial.

In [10]:
```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import deeptrack as dt

# Load exp data
predator_sequence = np.load(
    "../data/data_figure3/predator_sequence.npy"
)

prey_sequence = np.load(
    "../data/data_figure3/prey_sequence.npy"
)

coords_2d_predator = np.load(
    "../data/data_figure3/predator_2d_coords.npy"
)

coords_2d_prey = np.load(
    "../data/data_figure3/prey_2d_coords.npy"
)
```

2. Defining training dataset

2.1. Defining simulation parameters

We generate 15-frame sequences of simulated holgoraphic images to train the WAC-Net, where each image is of size 64 x 64 pixels. Each image contains plankton holograms of different properties as defined below.

In [11]:
```
variables = {
    "pix_size": 3.6, # in micro meters
    "radius_range": [1.5e-6, 10e-6],
    "ri_range": [1.35, 1.38],
    "z_range": [2300, 3000], #in microns
    "apod_val": 0.07, #Gaussian apodization value
}
```

2.2. Defining scatterer properties

Each plankton is a scatterer. We use the `Sphere` feature of DeepTrack to generate spherical scatterers. Since we are using lensless-holographic setup, planktons can be approximated as spherical objects. All the other properties are automatically filled from the variables defined above in the cell above.

2.2.1. Defining main plankton

The main plankton is the plankton that is always centered in a sequnce, and it is the plankton for which for which the dry mass and radius are predicted.

In [12]:
```
_sphere_main = dt.Sphere(
    position=(32, 32),
    position_unit="pixel",
    cam_pix_size=variables["pix_size"],
    radius=lambda: variables["radius_range"][0]
    + np.random.rand()
    * (variables["radius_range"][1] - variables["radius_range"][0]),
    refractive_index=lambda: variables["ri_range"][0]
    + np.random.rand() * (variables["ri_range"][1] - variables["ri_range"][0]),
    z=lambda: variables["z_range"][0] / variables["pix_size"]
    + np.random.rand()
    * (variables["z_range"][1] - variables["z_range"][0])
    / variables["pix_size"],
    find_me=True,
)


def get_position(previous_value):
    return previous_value + np.random.uniform(-1 / 8, 1 / 8, size=2)

sphere_main = dt.Sequential(_sphere_main, position=get_position)
```

2.2.2 Defining noise planktons

The noise planktons are planktons in the background.

In [13]:
```
_sphere_noise = dt.Sphere(
    position=lambda: np.random.rand(2) * 64,
    position_unit="pixel",
    cam_pix_size=_sphere_main.cam_pix_size,
    z=_sphere_main.z,
    radius=_sphere_main.radius,
    refractive_index=_sphere_main.refractive_index,
    find_me=False,
)


def get_position2(previous_value):
    return previous_value + np.random.uniform(0, 7, size=2)


sphere_noise = dt.Sequential(_sphere_noise, position=get_position2)
```

2.3. Defining the optical device

The scatterers are imaged with an optical device. We use the `Brightfield` feature of DeepTrack to define a microscope operating at `wavelength` of 633 nm.

In [14]:
```
optics = dt.Brightfield(
    wavelength=633e-9,
    NA=1,
    resolution=variables["pix_size"] * 1e-6,
    magnification=1,
    refractive_index_medium=1.33,
    apod_val=variables["apod_val"],
    upscale=4,
    aberration=lambda apod_val: dt.GaussianApodization(apod_val + np.random.uniform(-1,1)*0.01),
    output_region=(0, 0, 64, 64),
)
```

2.4. Defining noises

We add gaussian noise to the generated images with a blur factor.

In [15]:
```
from deeptrack.noises import Noise
from skimage.filters import gaussian
class Blurred_Gaussian(Noise):
    """Adds IID Gaussian noise to an image

    Parameters
    ----------
    mu : float
        The mean of the distribution.
    sigma : float
        The root of the variance of the distribution.
    """

    def __init__(self, mu=0, sigma=1,blur=2, **kwargs):
        super().__init__(mu=mu, sigma=sigma,blur=blur, **kwargs)

    def get(self, image, mu, sigma,blur, **kwargs):

        noisy_image = mu  + np.random.randn(*image.shape) * sigma
        noisy_image=gaussian(noisy_image,sigma=blur)
        noisy_image=image+noisy_image
        return noisy_image

noise = Blurred_Gaussian(mu=0, sigma= lambda: .025, blur=0.9+np.random.uniform(0,1)*0.1)
```

2.5. Defining number of planktons (main and noise)

The main plankton is always set to 1, and number of noise planktons is set to vary between 0 to 3.

In [16]:
```
sphere_main_no = lambda: np.random.randint(1, 2)
sphere_noise_no = lambda: np.random.randint(0, 3)

sample_normal = sphere_main ** sphere_main_no
sample_with_noise = sample_normal + sphere_noise ** sphere_noise_no
```

2.6. Combining all the properties defined above

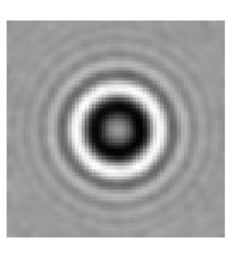
Passing all the features to the optical device to generate sample sequences.

In [17]:
```
image_formed = optics(sample_with_noise)

seq_length = 15
image_of_particles = dt.ConditionalSetFeature(
    on_true=dt.Sequence(image_formed, sequence_length=seq_length) + noise,
    on_false=dt.FlipUD(
        dt.FlipLR(
            dt.FlipDiagonal(
                dt.Sequence(image_formed, sequence_length=seq_length)
            )
        )
    )
    + noise,
    condition="skip_aug",
    skip_aug=False,
)
```

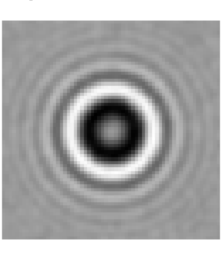
2.7. Visualising an example sequence

In [18]:
```
image_of_particles.update(skip_aug="False").plot(cmap="gray")
```



Once Loop Reflect

Out[18]:
```
<matplotlib.animation.ArtistAnimation at 0x7fef76974fd0>
```



3. Creating target values

3.1. Vertical position values

Function to generate normalized z values as outputs.

In [19]:
```
def get_z(image):
    z = image[0].get_property("z")
    z = (z - variables["z_range"][0] / variables["pix_size"]) / (
        variables["z_range"][1] / variables["pix_size"]
        - variables["z_range"][0] / variables["pix_size"]
    )
    return z
```

4. Training setup

4.1. Define WAC-Net using keras with tensorflow backend

In [20]:
```
from tensorflow import keras

Sequential = keras.models.Sequential
Model = keras.models.Model
Dense = keras.layers.Dense
# Dropout = keras.layers.Dropout
Conv = keras.layers.Conv2D
Conv1D = keras.layers.Conv1D
ConvL = keras.layers.LocallyConnected2D
Pool = keras.layers.MaxPooling2D
Input = keras.layers.Input
Concat = keras.layers.Concatenate
TimeDistributed = keras.layers.TimeDistributed
Flatten = keras.layers.Flatten
Lambda = keras.layers.Lambda
K = keras.backend


model = Sequential()
model.add(
    (
        Conv(
            32,
            kernel_size=3,
            strides=1,
            activation="relu",
            input_shape=(64, 64, 1),
        )
    )
)
model.add(Pool(2))
model.add((Conv(64, kernel_size=3, strides=1, activation="relu")))
model.add(Pool(2))
model.add((Conv(128, kernel_size=3, strides=1, activation="relu")))
model.add(Pool(2))
model.add((Conv(256, kernel_size=3, strides=1, activation="relu")))
model.add((Flatten()))
model.add((Dense(128, activation="relu")))
model.add((Dense(128, activation="relu")))

stack = Input(model.input_shape)
vectors = TimeDistributed(model)(
    stack
)  # time distributed applies a layer to every temporal slice of the input
weights = Conv1D(128, 1, padding="same")(vectors)
weights = Conv1D(128, 1, padding="same")(weights)
weights = Conv1D(1, 1, padding="same")(weights)


def merge_function(tensors):
    x = tensors[0]
    weights = tensors[1]
    weights = K.softmax(weights, axis=1)
    merged = K.sum(x * weights, axis=1)
    return merged


merge_layer = Lambda(merge_function)

merged = merge_layer([vectors, weights])

merged = Dense(32, activation="relu")(merged)
merged = Dense(32, activation="relu")(merged)
out = Dense(1)(merged)
model = Model(stack, out)

model.summary()
```

```
Model: "functional_1"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, None, 64, 64 0
__________________________________________________________________________________________________
time_distributed (TimeDistribut (None, None, 128)    928768      input_1[0][0]
__________________________________________________________________________________________________
conv1d (Conv1D)                 (None, None, 128)    16512       time_distributed[0][0]
__________________________________________________________________________________________________
conv1d_1 (Conv1D)               (None, None, 128)    16512       conv1d[0][0]
__________________________________________________________________________________________________
conv1d_2 (Conv1D)               (None, None, 1)      129         conv1d_1[0][0]
__________________________________________________________________________________________________
lambda (Lambda)                 (None, 128)          0           time_distributed[0][0]
                                                                 conv1d_2[0][0]
__________________________________________________________________________________________________
dense_2 (Dense)                 (None, 32)           4128        lambda[0][0]
__________________________________________________________________________________________________
dense_3 (Dense)                 (None, 32)           1056        dense_2[0][0]
__________________________________________________________________________________________________
dense_4 (Dense)                 (None, 1)            33          dense_3[0][0]
==================================================================================================
Total params: 967,138
Trainable params: 967,138
Non-trainable params: 0
__________________________________________________________________________________________________
```

In [21]:
```
model.compile(tf.keras.optimizers.Adam(lr=0.0001, amsgrad=True), loss="mae")
```

4.2. Defining batch function

In [22]:
```
def batch_function(image):
    for i in range(len(image)):
        image[i] = image[i] / np.median(image[i]) - 1
    return image
```

4.3. Defining generator

The generator generates `2000` image sequences before the training begins, and continous to generate another `2000` sample sequences during the training process.

In [23]:
```
generator = dt.generators.ContinuousGenerator(
    image_of_particles,
    get_z,
    batch_size=64,
    batch_function=batch_function,
    min_data_size=2000,
    max_data_size=4000,
    ndim=5,
)
```

5. Training the model

Set the `TRAIN_MODEL` = `True` to train the model from scratch. Set the `TRAIN_MODEL` = `False` to load a pretrained model.

In [24]:
```
TRAIN_MODEL = False
```

5.1. Generating validation data

Skip this step if would not like to generate validation data.

In [25]:
```
if TRAIN_MODEL:

    print("Generating validation data...")
    b = []
    l = []
    for i in tqdm(range(1000)):
        im = image_of_particles.update(skip_aug=False).resolve()
        b.append(batch_function(im))
        l.append(get_z(im))
    b = np.array(b)
    l = np.array(l)
```

5.2. Start the training

Set the `TRAIN_MODEL` to True to train the network from scratch.

In [26]:
```
if TRAIN_MODEL:

    with generator:
        history = model.fit(
            generator, epochs=1000, steps_per_epoch=16, validation_data=(b, l)
        )

else:
    model.load_weights("../pre-trained-models/WACNet_vertical_positions.h5")
```

6. Testing the trained model on experimental sequences

6.1. Normalising the experimental images

Functions normalise the images, and to convert predicted dry mass values to real values.

In [27]:
```
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 [28]:
```
def real_z(p, a=700, b=2300):
    return (p*a+b)
```

6.2. Checking predictions

In [29]:
```
prediction_predator = model.predict(
    Normalise(
        predator_sequence,
        batch = 1
    )
)

prediction_prey = model.predict(
    Normalise(
        prey_sequence,
        batch = 1
    )
)
```

In [30]:
```
z_predator = real_z(prediction_predator[:,0])
z_prey = real_z(prediction_prey[:,0])
```

In [31]:
```
feeding_at = 219

fig = plt.figure(figsize=(10,10))
ax = fig.gca(projection='3d')


ax.plot(coords_2d_predator[:,0][:feeding_at], coords_2d_predator[:,1][:feeding_at], z_predator[:feeding
_at], label='$\it{Oxyrrhis\ marina}$ pre-feeding',
        color="tab:orange", alpha=0.5, linestyle="solid", linewidth=2)

ax.plot(coords_2d_prey[:,0][:feeding_at], coords_2d_prey[:,1][:feeding_at], z_prey[:feeding_at], label=
'$\it{Dunaliella\ tertiolecta}$ pre-feeding',
        color="tab:blue", alpha=0.5, linestyle="solid", linewidth=2)

ax.plot(coords_2d_predator[:,0][feeding_at:], coords_2d_predator[:,1][feeding_at:], z_predator[feeding_
at:], label='$\it{Oxyrrhis\ marina}$ post-feeding',
        color="darkorange", alpha=0.5, linestyle="solid", linewidth=2)

plt.legend()

ax.set_xlabel('\n\n\n Position X')
ax.set_ylabel('\n\n\n Position Y')
ax.set_zlabel('\n\n\n Position Z ($\mu m$)')

ax.azim = -50
ax.elev = 40
ax.dist = 10

plt.show()
```