Geometric Computer Vision: Final Project

This notebook contains a revisited implementation of the paper: **Shape Non-rigid Kinematics (SNK): A Zero-Shot Method for Non-Rigid Shape Matching via Unsupervised Functional Map Regularized Reconstruction** by Attaiki and Ovsjanikov (2024).

Imports

```
from pyFM.functional import FunctionalMapping
import numpy as np
import trimesh
from pyFM.mesh import TriMesh
import torch
from torch_geometric.data import Batch
from diffusion_net import DiffusionData, DiffusionOperatorsTransform,
DiffusionNet
from prism_decoder import PrismDecoder
import torch.optim as optim
from tqdm import tqdm
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d.art3d import Poly3DCollection
from matplotlib import cm
from loss import PrismRegularizationLoss
```

Load meshes

Let's first load the meshes of two dogs modified (non-rigid deformation using Blender):

```
# load some meshes
obj1 = r"./Samples/dog_small.obj"
obj2 = r"./Samples/dog_small_after_torture.obj"
mesh1, mesh2 = TriMesh(obj1), TriMesh(obj2)
```

Compute correspondance from mesh2 to mesh1 using functional maps

I chose the pyFM package investigated in HW3 to compute a correspondance map between the meshes, using WKS descriptors:

```
process_params = {
    'n_ev': (70, 70),  # Number of eigenvalues on source and Target
    'subsample_step': 20,  # In order not to use too many descriptors
    'descr_type': 'WKS',  # WKS or HKS
}
model = FunctionalMapping(mesh1, mesh2)
```

```python
model.preprocess(**process_params, verbose=False)
fit_params = {
    'w_descr': 1e0,
    'w_lap': 1e-2,
    'w_dcomm': 1e-1,
    'w_orient': 0
}
model.fit(**fit_params, verbose=False)
p2p_21 = model.get_p2p(n_jobs=1)
```

Visualization using meshplot package

```python
import meshplot as mp

def double_plot_mp(myMesh1,myMesh2,cmap1=None,cmap2=None):
    p = mp.plot(myMesh1.vertlist, myMesh1.facelist, c=cmap1)
    v2_translated = myMesh2.vertlist.copy()
    f2_translated = myMesh2.facelist.copy()
    myMesh2_translated = TriMesh(v2_translated, f2_translated)
    myMesh2_translated.vertlist[:,0] =
myMesh2_translated.vertlist[:,0] + 30
    p.add_mesh(myMesh2_translated.vertlist,
myMesh2_translated.facelist, c=cmap2)

def visu(vertices):
    min_coord,max_coord =
np.min(vertices,axis=0,keepdims=True),np.max(vertices,axis=0,keepdims=
True)
    cmap = (vertices-min_coord)/(max_coord-min_coord)
    return cmap

cmap1 = visu(mesh1.vertlist); cmap2 = cmap1[p2p_21]
double_plot_mp(mesh1,mesh2,cmap1,cmap2)
```

{"model_id":"fc1770e0779940718bef04bff3f18226","version_major":2,"vers
ion_minor":0}

Compute latent vector

Following section 4.2 in the paper, we compute a latent vector (of length d1) per feature using DiffusionNet++ module, then apply max pooling to get a vector l of length d1.

Then we aim to reconstruct the first shape by concatenating l to each feature of the second mesh and passing those to the decoder.

```python
def compute_l(my_batch, diffusion_net):
    my_batch.x = my_batch.pos.clone()  # set the input features to the
positions
    output = diffusion_net(my_batch)
```

```
    l = output.x.max(dim=0).values
    return l

def reconstruct_s2(my_batch2, v2_t, l, decoder):
    l_expanded = l.unsqueeze(0).repeat(v2_t.shape[0],1)
    my_batch2.x = torch.cat((v2_t,l_expanded),dim=1) #.unsqueeze(0)
    # my_batch2.pos = my_batch2.pos.unsqueeze(0)
#my_batch2.pos.clone()   .clone() # set the input features to the
positions
    s3 = decoder(my_batch2)
    return s3
```

Prepare first mesh for compatibility with DiffusionNet++ model

```
mesh1_diff = trimesh.load(obj1)
v1, f1 = np.array(mesh1.vertices), np.array(mesh1.faces)
v1_t = torch.from_numpy(v1)
f1_t = torch.from_numpy(f1)
data1 = DiffusionData(pos=v1_t, face=f1_t.T)
diffusion_transform = DiffusionOperatorsTransform(n_eig=50)  #97
compute the diffusion net operators with 97 eigenvalues
data1 = diffusion_transform(data1)
my_batch = Batch.from_data_list([data1])
```

Prepare second mesh for compatibility with DiffusionNet++ model

```
mesh2_diff = trimesh.load(obj2)
v2, f2 = np.array(mesh2.vertices), np.array(mesh2.faces)
data2 = DiffusionData(pos=torch.from_numpy(v2),
face=torch.from_numpy(f2).T)
diffusion_transform = DiffusionOperatorsTransform(n_eig=50)  #97
compute the diffusion net operators with 97 eigenvalues
data2 = diffusion_transform(data2)
my_batch2 = Batch.from_data_list([data2])
my_batch2.pos = my_batch2.pos.unsqueeze(0)
#######
v2_t = torch.Tensor(v2)
```

Make parameters differentiable - for backward propagation

```
my_batch.pos.requires_grad = True
v2_t.requires_grad = True
my_batch2.pos.requires_grad = True
```

Prepare visualization functions

```
def double_plot(myMesh1, myMesh2, cmap1=None, cmap2=None,
title1='Mesh1',title2='Mesh2'):
```

```
    fig = plt.figure(figsize=plt.figaspect(0.5))
    ax1 = fig.add_subplot(1, 2, 1, projection='3d')
    ax1.plot_trisurf(myMesh1.vertlist[:, 0], myMesh1.vertlist[:, 1],
myMesh1.vertlist[:, 2],
                     triangles=myMesh1.facelist, cmap='viridis',
facecolors=cmap1)
    ax1.set_title(title1)
    ax2 = fig.add_subplot(1, 2, 2, projection='3d')
    ax2.plot_trisurf(myMesh2.vertlist[:, 0], myMesh2.vertlist[:, 1],
myMesh2.vertlist[:, 2],
                     triangles=myMesh2.facelist, cmap='viridis',
facecolors=cmap2)
    ax2.set_title(title2)

def visu_face_colors(s1_faces_raw, s1_faces, s2_faces, s3_faces):
    cmap = cm.get_cmap('viridis', s3_faces.shape[0])  # Use a colormap
with 500 distinct colors
    face_colors = cmap(np.linspace(0, 1, s3_faces.shape[0]))

    average_z = np.mean(s2_faces[:, :, 2], axis=1)
    sorted_indices = np.argsort(average_z)

    sorted_s3_faces = s3_faces[sorted_indices]
    sorted_s2_faces = s2_faces[sorted_indices]
    sorted_s1_faces = s1_faces[sorted_indices]
    fig = plt.figure()
    ax1 = fig.add_subplot(131, projection='3d')
    ax2 = fig.add_subplot(132, projection='3d')
    ax3 = fig.add_subplot(133, projection='3d')
    for i, face in enumerate(s3_faces):
        # poly3d = [[vertices[vert_idx] for vert_idx in face]]
        poly3d_1 = [sorted_s1_faces[i]]
        poly3d_2 = [sorted_s2_faces[i]]
        poly3d_1_raw = [s1_faces_raw[i]]
        poly3d_3 = [sorted_s3_faces[i]]
        ax1.add_collection3d(Poly3DCollection(poly3d_1,
facecolors=face_colors[i], linewidths=1, edgecolors=None, alpha=.8))
        ax1.add_collection3d(Poly3DCollection(poly3d_1_raw,
facecolors='b', linewidths=1, edgecolors=None, alpha=.1))
        ax2.add_collection3d(Poly3DCollection(poly3d_2,
facecolors=face_colors[i], linewidths=1, edgecolors=None, alpha=.8))
        ax3.add_collection3d(Poly3DCollection(poly3d_3,
facecolors=face_colors[i], linewidths=1, edgecolors=None, alpha=.8))
    ax1.set_xlim([s1_faces[:,:,0].min(), s1_faces[:,:,0].max()])
    ax1.set_ylim([s1_faces[:,:,1].min(), s1_faces[:,:,1].max()])
    ax1.set_zlim([s1_faces[:,:,2].min(), s1_faces[:,:,2].max()])
    ax2.set_xlim([s2_faces[:,:,0].min(), s2_faces[:,:,0].max()])
    ax2.set_ylim([s2_faces[:,:,1].min(), s2_faces[:,:,1].max()])
    ax2.set_zlim([s2_faces[:,:,2].min(), s2_faces[:,:,2].max()])
```

```
    ax3.set_xlim([s3_faces[:,:,0].min(), s3_faces[:,:,0].max()])
    ax3.set_ylim([s3_faces[:,:,1].min(), s3_faces[:,:,1].max()])
    ax3.set_zlim([s3_faces[:,:,2].min(), s3_faces[:,:,2].max()])
    plt.show()
```

Handling face matching for visualization

```
def compute_centroid(face):
    return np.mean(face, axis=0)

def find_closest_faces(lf1, lf2):
    centroids_lf1 = np.array([compute_centroid(face) for face in lf1])
    centroids_lf2 = np.array([compute_centroid(face) for face in lf2])

    closest_faces = []
    closest_faces_idx = []

    for centroid in centroids_lf2:
        distances = np.linalg.norm(centroids_lf1 - centroid, axis=1)
        closest_face_idx = np.argmin(distances)
        while closest_face_idx in closest_faces_idx:
            distances[closest_face_idx] = max(distances) + 1
            closest_face_idx = np.argmin(distances)
        closest_faces.append(lf1[closest_face_idx])
        closest_faces_idx.append(closest_face_idx)
    return closest_faces_idx

v1s = my_batch.pos.reshape(-1, 3)
f1s = my_batch.face.t()
s1_faces_tmp = v1s[f1s].detach().numpy()
```

Initialization of the models (DiffusionNet, PrismDecoder)

```
L_SPACE_SIZE = 42
diffusion_net = DiffusionNet(3, L_SPACE_SIZE)
decoder = PrismDecoder(v1.shape[1]+L_SPACE_SIZE, v1.shape[0])
```

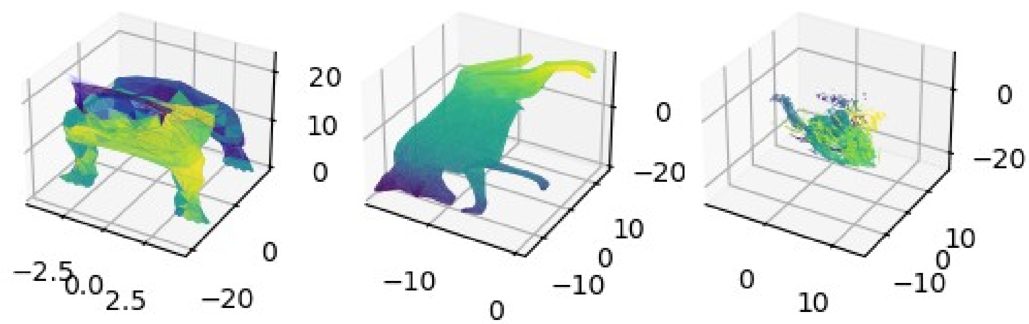
Training process

```
# %debug
lambda_E = 30
losses_MSE = []
losses_energy = []
losses = []
get_energy_loss = PrismRegularizationLoss(100)
optimizer_diffnet = optim.AdamW(diffusion_net.parameters() ,lr=0.001,
weight_decay=0.001)
optimizer_decoder = optim.AdamW(decoder.parameters() ,lr=0.001,
weight_decay=0.001)
```

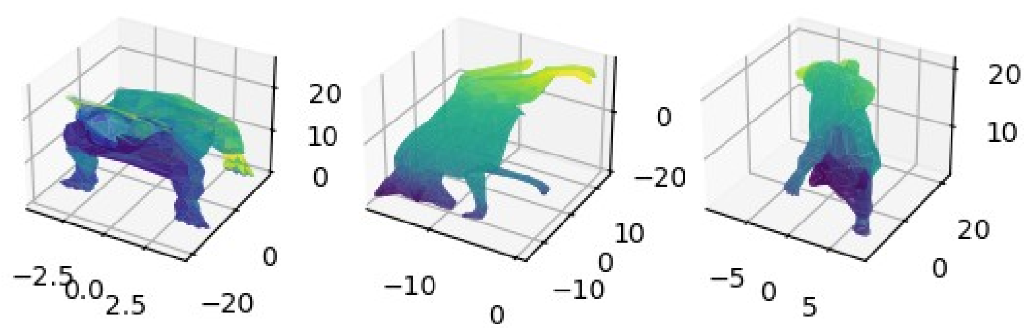
```
for epoch in (pbar:=tqdm(range(2000))):
    l = compute_l(my_batch, diffusion_net)
    l.retain_grad()
    s3 = reconstruct_s2(my_batch2, v2_t, l, decoder)
    s3.features.retain_grad()
    v1_remapped = v1[p2p_21]
    loss =
torch.nn.functional.mse_loss(torch.Tensor(v1_remapped),s3.features)
    loss_E = get_energy_loss(s3.transformed_prism, s3.rotations,
s3.pos.reshape(-1, 3), s3.face)
    total_loss = loss + loss_E*lambda_E
    losses_MSE.append(loss.detach())
    losses_energy.append(loss_E.detach())
    losses.append(total_loss.detach())
    pbar.set_description(f"{loss.detach():3f}")
    total_loss.retain_grad()
    total_loss.backward()
    # import ipdb; ipdb.set_trace()
    optimizer_diffnet.step()
    optimizer_diffnet.zero_grad()
    optimizer_decoder.step()
    optimizer_decoder.zero_grad()
    if (epoch%20 == 0 and epoch<=101) or epoch%100 == 0:
        print(f'Epoch {epoch}: MSE loss = {loss}')
        print(f'Epoch {epoch}: Energy loss = {loss_E}')
        verts = my_batch2.pos.reshape(-1, 3)
        faces = my_batch2.face.t()
        s2_faces = verts[faces].detach().numpy()
        s3_faces = s3.transformed_prism.detach().squeeze(0).numpy()
        closest_faces_idx = find_closest_faces(s1_faces_tmp, s3_faces)
#find_closest_faces(s3_faces, s1_faces_tmp)
        s1_faces = s1_faces_tmp[closest_faces_idx]
        visu_face_colors(s1_faces_tmp, s1_faces, s2_faces, s3_faces)
        plt.show()
```

```
  0%|
| 0/2000 [00:00<?, ?it/s]C:\Users\Hadassa-Port\AppData\Local\Temp\
ipykernel_12508\321993680.py:15: UserWarning: Using a target size
(torch.Size([1, 487, 3])) that is different to the input size
(torch.Size([487, 3])). This will likely lead to incorrect results due
to broadcasting. Please ensure they have the same size.
  loss =
torch.nn.functional.mse_loss(torch.Tensor(v1_remapped),s3.features)
C:\Users\Hadassa-Port\Desktop\hadassa\Toar 2\Semester 1\Geometric
Computer Vision\SNK\loss.py:28: UserWarning: Using torch.cross without
specifying the dim arg is deprecated.
Please either pass the dim explicitly or simply use
torch.linalg.cross.
The default value of dim will change to agree with that of
linalg.cross in a future release. (Triggered internally at ..\aten\
```

```
src\ATen\native\Cross.cpp:66.)
  normal = torch.cross(edge1, edge2)
380.823242:   0%|
| 0/2000 [00:00<?, ?it/s]

Epoch 0: MSE loss = 380.8232421875
Epoch 0: Energy loss = 55.170536041259766

C:\Users\Hadassa-Port\AppData\Local\Temp\
ipykernel_12508\2963957283.py:13: MatplotlibDeprecationWarning: The
get_cmap function was deprecated in Matplotlib 3.7 and will be removed
two minor releases later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  cmap = cm.get_cmap('viridis', s3_faces.shape[0])  # Use a colormap
with 500 distinct colors
```

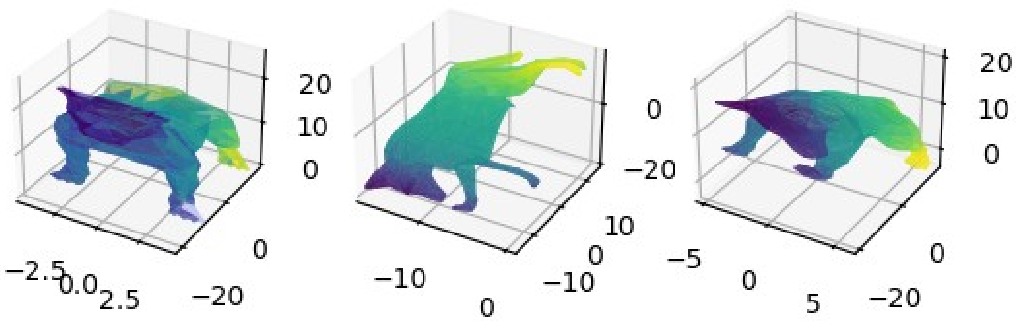



```
37.519310:   1%|█
| 20/2000 [00:48<33:17,  1.01s/it]

Epoch 20: MSE loss = 37.519309997558594
Epoch 20: Energy loss = 0.06417781859636307
```

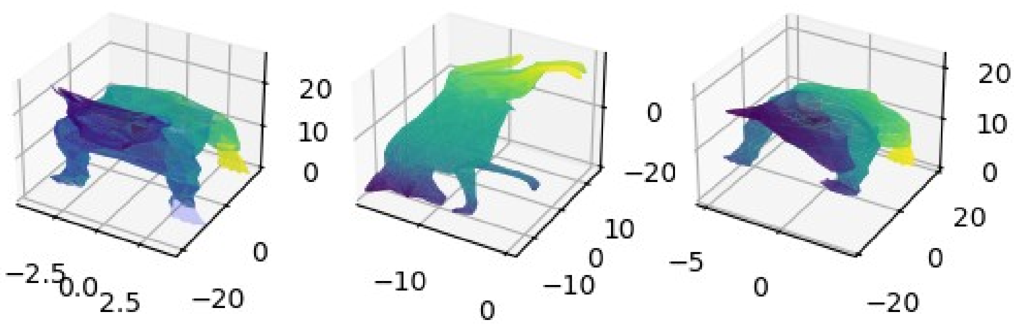



```
18.741827:   2%|██
| 40/2000 [01:34<47:36,  1.46s/it]
```

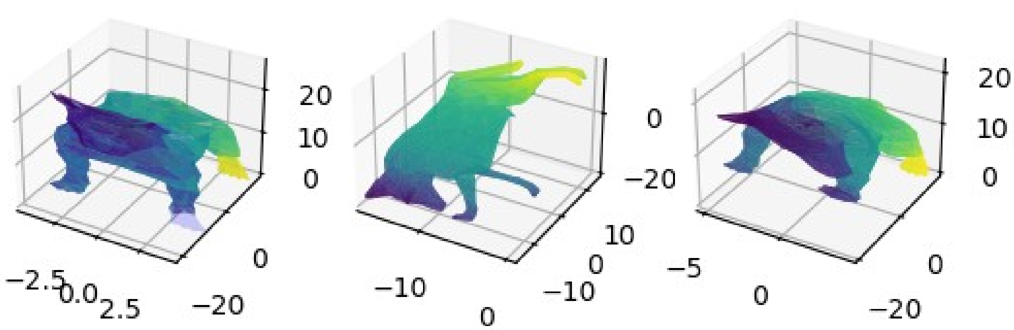
```
Epoch 40: MSE loss = 18.7418270111084
Epoch 40: Energy loss = 0.002584312343969941
```



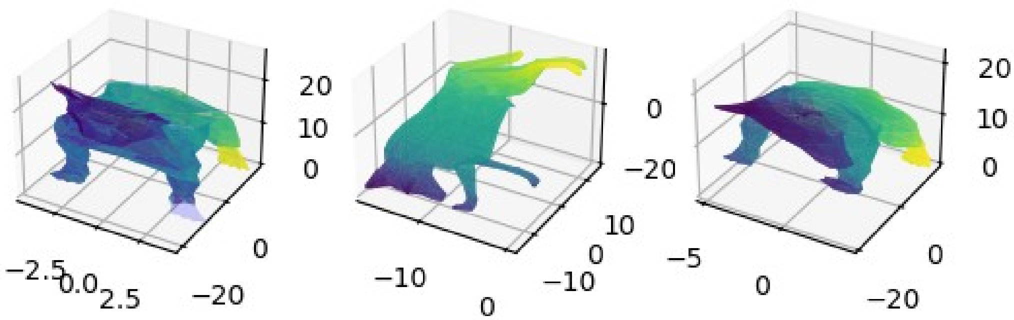
```
16.039995:   3%|
| 60/2000 [02:10<32:58,  1.02s/it]

Epoch 60: MSE loss = 16.039995193481445
Epoch 60: Energy loss = 0.00724763935431838
```



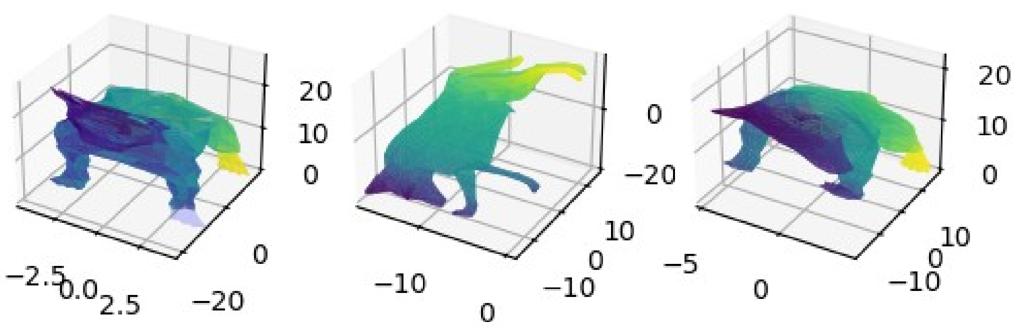
```
15.875034:   4%|
| 80/2000 [02:40<32:13,  1.01s/it]

Epoch 80: MSE loss = 15.87503433227539
Epoch 80: Energy loss = 0.006988008506596088
```



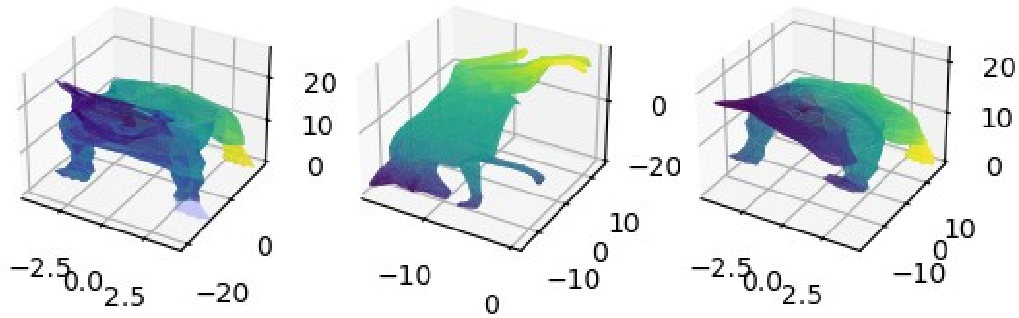
```
15.714131:   5%|███████
| 100/2000 [03:11<32:33,  1.03s/it]

Epoch 100: MSE loss = 15.714131355285645
Epoch 100: Energy loss = 0.006078184582293034
```



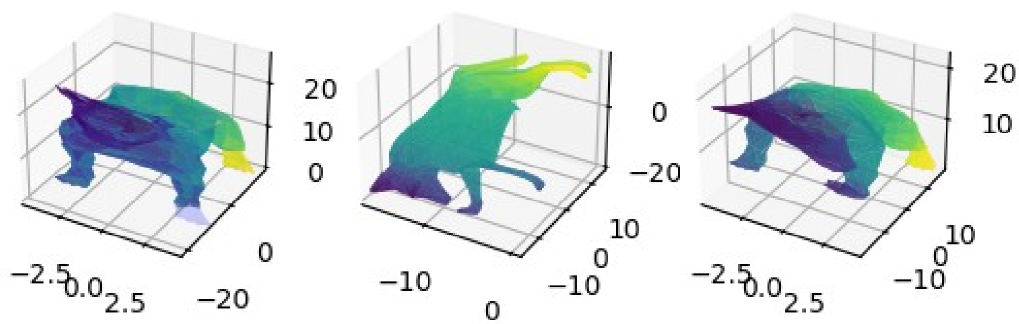

```
14.708385:  10%|██████████████
| 200/2000 [05:04<31:01,  1.03s/it]

Epoch 200: MSE loss = 14.708385467529297
Epoch 200: Energy loss = 0.01923668012022972
```



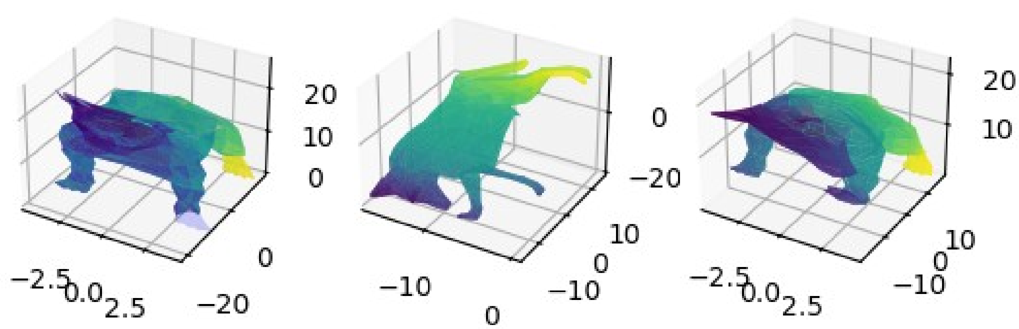

```
14.443155:  15%|█████████████████████
| 300/2000 [07:04<29:41,  1.05s/it]

Epoch 300: MSE loss = 14.443155288696289
Epoch 300: Energy loss = 0.02276437170803547
```




```
14.251207:  20%|
| 400/2000 [08:58<25:51,  1.03it/s]

Epoch 400: MSE loss = 14.25120735168457
Epoch 400: Energy loss = 0.024506928399205208
```

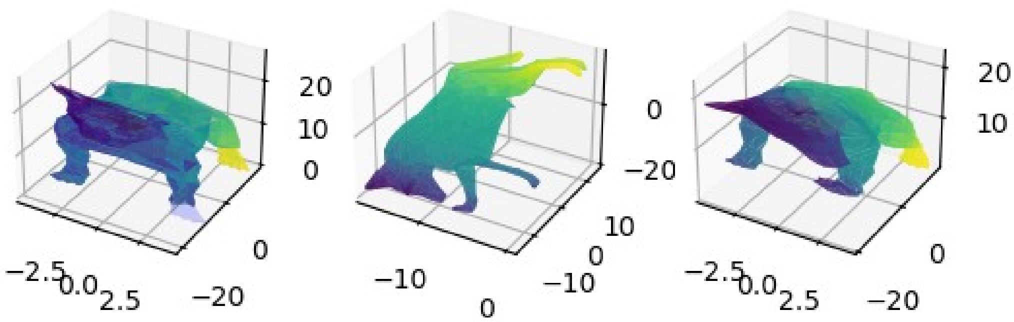



```
14.017374:  25%|
| 500/2000 [10:53<23:57,  1.04it/s]

Epoch 500: MSE loss = 14.017374038696289
Epoch 500: Energy loss = 0.028628913685679436
```

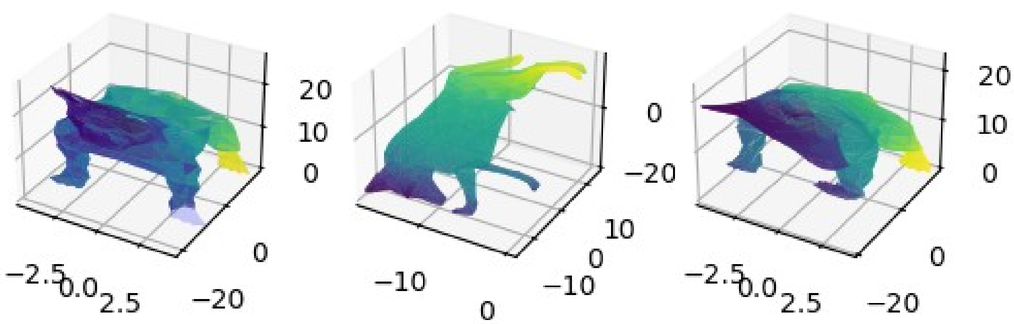



```
13.603838:  30%|
| 600/2000 [12:47<22:35,  1.03it/s]
```

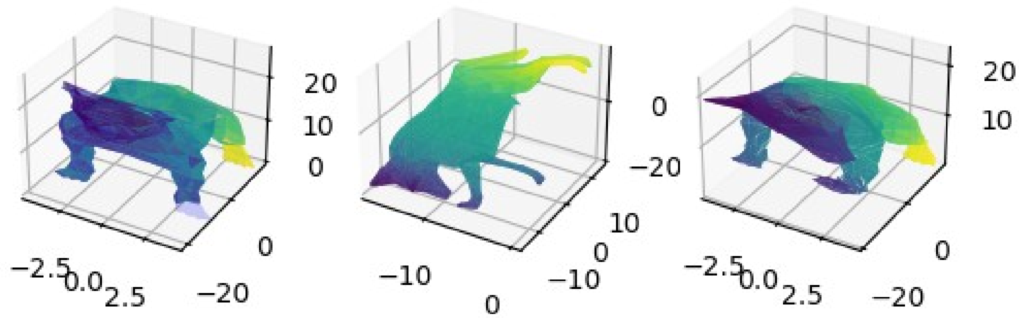
```
Epoch 600: MSE loss = 13.603837966918945
Epoch 600: Energy loss = 0.032199397683143616
```



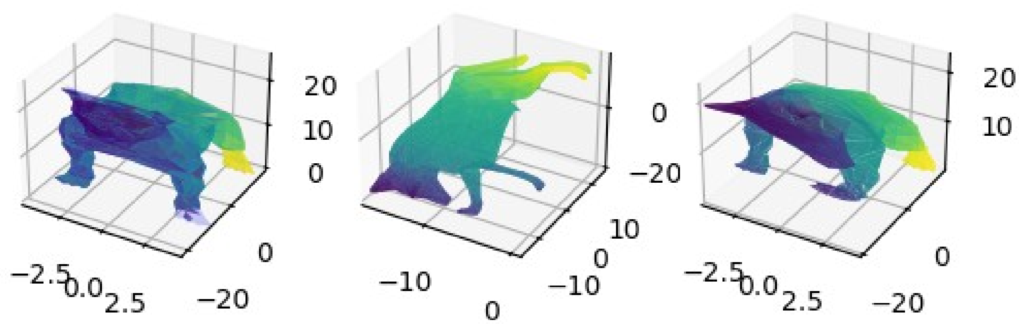

```
13.452585:  35%|
| 700/2000 [14:36<22:22,  1.03s/it]

Epoch 700: MSE loss = 13.452585220336914
Epoch 700: Energy loss = 0.03310574218630791
```



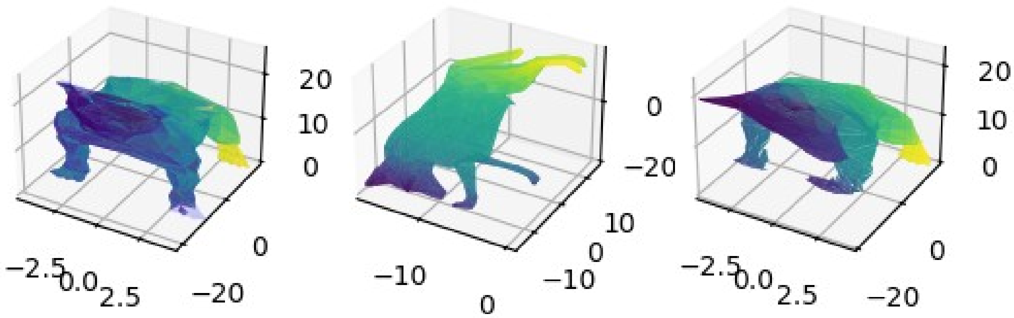

```
12.586988:  40%|
| 800/2000 [16:26<22:13,  1.11s/it]

Epoch 800: MSE loss = 12.58698844909668
Epoch 800: Energy loss = 0.0529869943857193
```



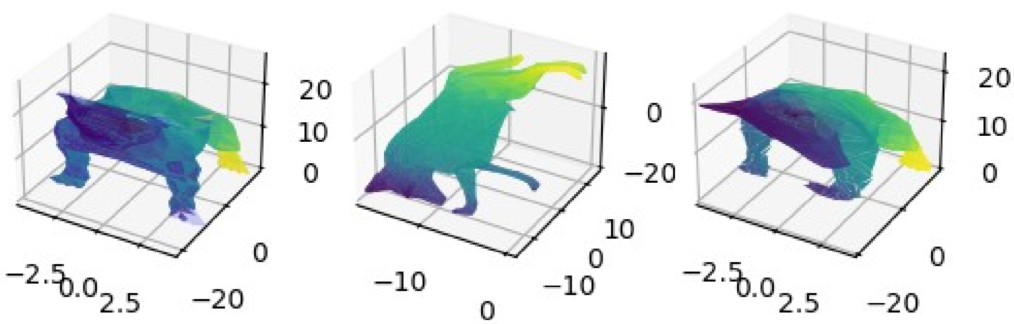

```
12.083807:  45%|
| 900/2000 [18:20<19:17,  1.05s/it]

Epoch 900: MSE loss = 12.083806991577148
Epoch 900: Energy loss = 0.05478142201900482
```



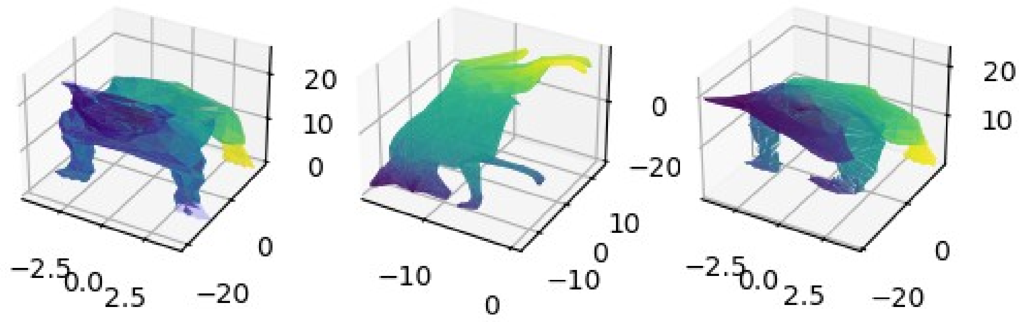

```
11.784428:  50%|
| 1000/2000 [20:11<16:32,  1.01it/s]

Epoch 1000: MSE loss = 11.784427642822266
Epoch 1000: Energy loss = 0.05672043561935425
```



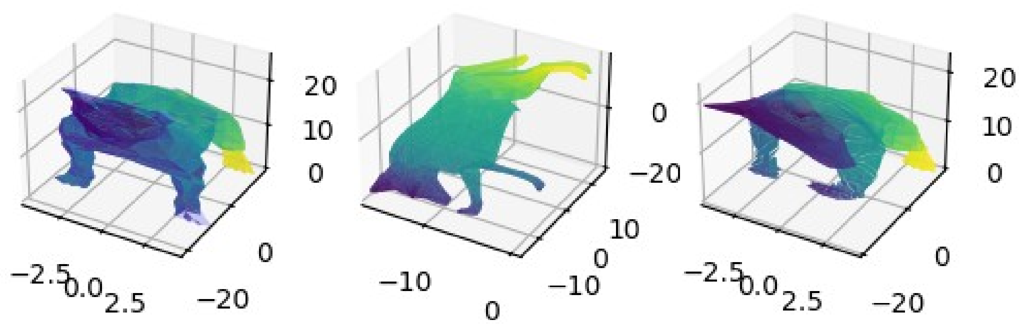
```
11.695845:  55%|
| 1100/2000 [22:26<20:13,  1.35s/it]

Epoch 1100: MSE loss = 11.695844650268555
Epoch 1100: Energy loss = 0.05680251121520996
```



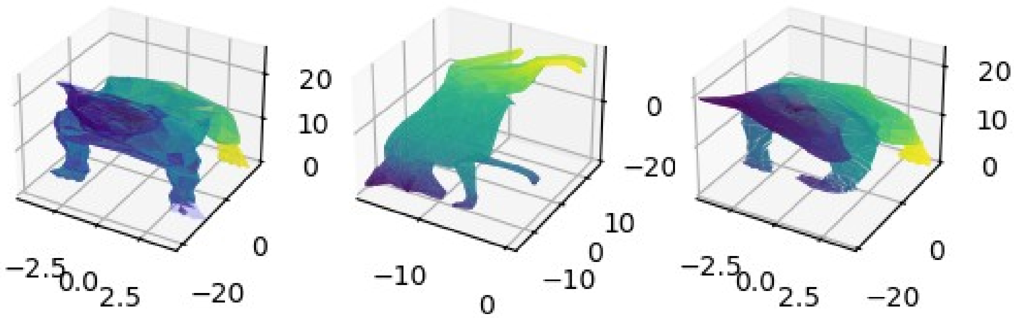
```
11.427905:  60%|
| 1200/2000 [24:51<24:02,  1.80s/it]

Epoch 1200: MSE loss = 11.427905082702637
Epoch 1200: Energy loss = 0.06552743166685104
```



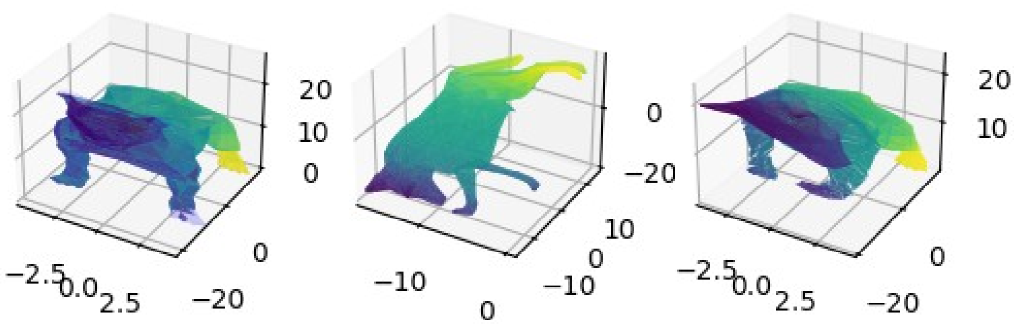

```
11.417137:  65%|
```
[redacted]
```
| 1300/2000 [27:07<11:57,  1.03s/it]

Epoch 1300: MSE loss = 11.417137145996094
Epoch 1300: Energy loss = 0.0595039464533329
```



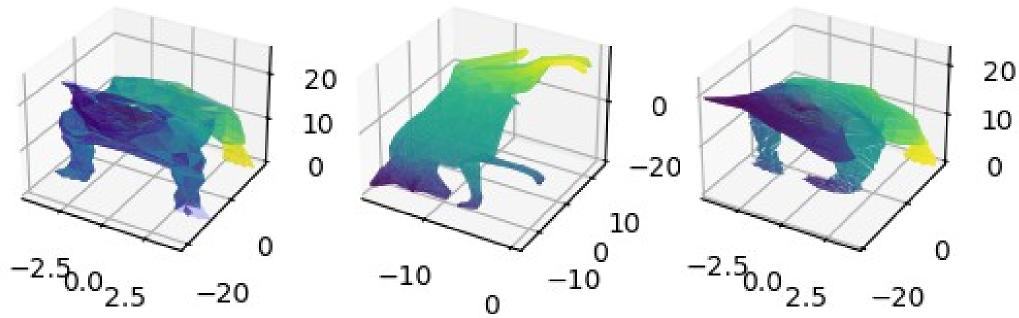

```
11.263186:  70%|
```
[redacted]
```
| 1400/2000 [28:56<10:09,  1.02s/it]

Epoch 1400: MSE loss = 11.263185501098633
Epoch 1400: Energy loss = 0.06322402507066727
```



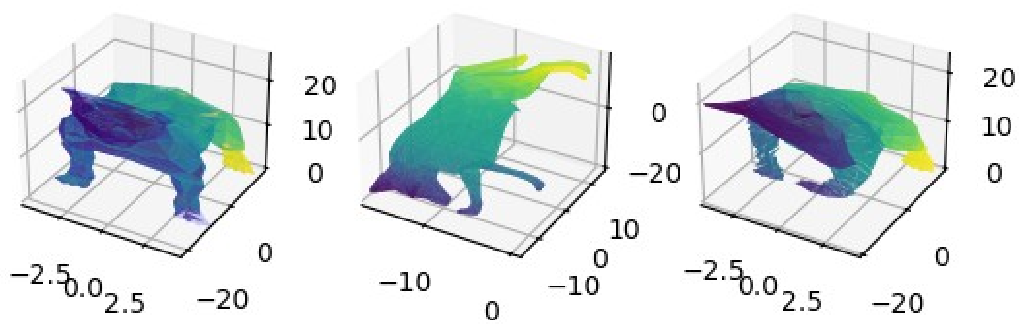

```
11.132992:  75%|
[redacted]
| 1500/2000 [30:49<08:45,  1.05s/it]

Epoch 1500: MSE loss = 11.132991790771484
Epoch 1500: Energy loss = 0.06326287239789963
```



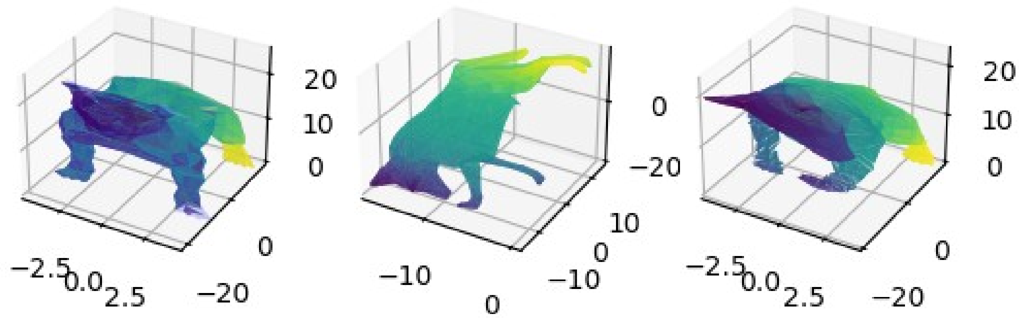

```
11.285318:  80%|
[redacted]
| 1600/2000 [32:40<06:39,  1.00it/s]

Epoch 1600: MSE loss = 11.285318374633789
Epoch 1600: Energy loss = 0.05605860054492950 4
```



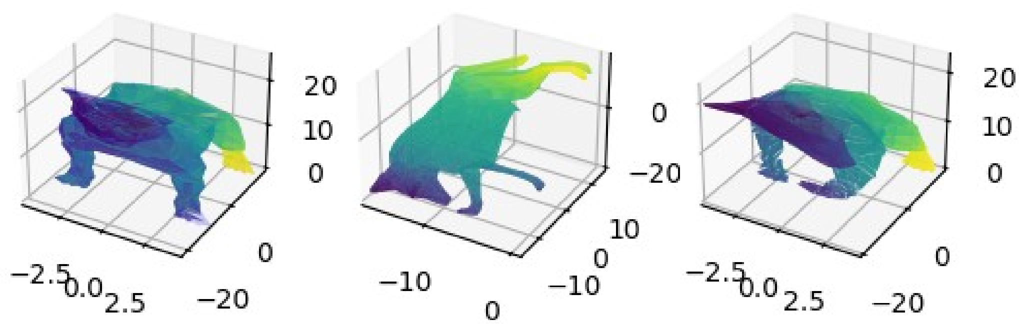

```
11.038894:  85%|
[redacted]
| 1700/2000 [34:30<04:51,  1.03it/s]

Epoch 1700: MSE loss = 11.038893699645996
Epoch 1700: Energy loss = 0.05881454795598984
```




```
10.967781:  90%|
[redacted]
| 1800/2000 [36:20<03:22,  1.01s/it]

Epoch 1800: MSE loss = 10.967781066894531
Epoch 1800: Energy loss = 0.062212999910116196
```




```
10.702518:  95%|[redacted]| 1900/2000 [38:13<01:37,  1.03it/s]

Epoch 1900: MSE loss = 10.702518463134766
Epoch 1900: Energy loss = 0.06658665835857391
```

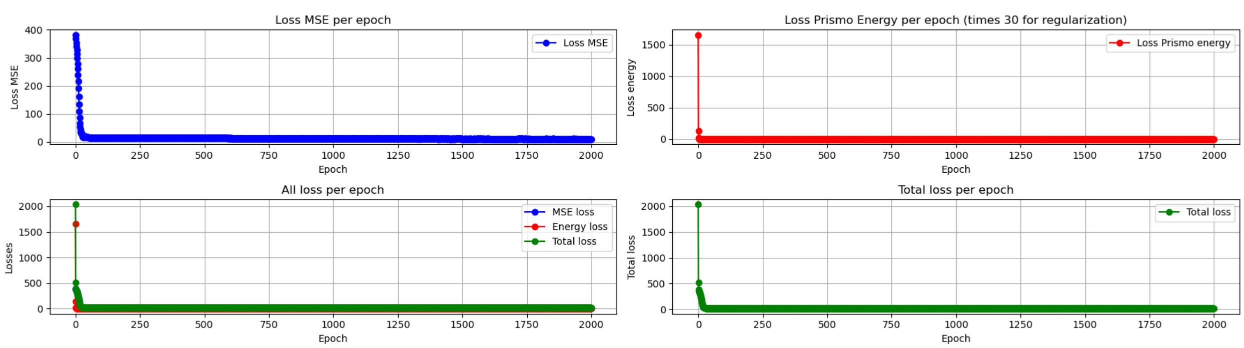



```
10.562922: 100%|[redacted]| 2000/2000 [40:08<00:00,  1.20s/it]
```

Plot the loss functions

```
# Create the figure and subplots
fig, axs = plt.subplots(2, 2, figsize=(18, 5))
l_energy = [lambda_E*a for a in losses_energy]
# Plot MSE loss
axs[0,0].plot(range(len(losses_MSE)), losses_MSE, label='Loss MSE',
marker='o', color='b')
axs[0,0].set_xlabel('Epoch'); axs[0,0].set_ylabel('Loss MSE')
axs[0,0].set_title('Loss MSE per epoch'); axs[0,0].legend();
axs[0,0].grid(True)
```

```
# Plot Energy loss
axs[0,1].plot(range(len(losses_energy)), l_energy, label='Loss Prismo
energy', marker='o', color='r')
axs[0,1].set_xlabel('Epoch'); axs[0,1].set_ylabel('Loss energy')
axs[0,1].set_title(f'Loss Prismo Energy per epoch (times {lambda_E}
for regularization)'); axs[0,1].legend(); axs[0,1].grid(True)

# Plot total loss
axs[1,0].plot(range(len(losses_MSE)), losses_MSE, label='MSE loss',
marker='o', color='b')
axs[1,0].plot(range(len(l_energy)), l_energy, label='Energy loss',
marker='o', color='r')
axs[1,0].plot(range(len(losses)), losses, label='Total loss',
marker='o', color='g')
axs[1,0].set_xlabel('Epoch'); axs[1,0].set_ylabel('Losses')
axs[1,0].set_title('All loss per epoch'); axs[1,0].legend();
axs[1,0].grid(True)

# Plot total loss
axs[1,1].plot(range(len(losses)), losses, label='Total loss',
marker='o', color='g')
axs[1,1].set_xlabel('Epoch'); axs[1,1].set_ylabel('Total loss')
axs[1,1].set_title('Total loss per epoch'); axs[1,1].legend();
axs[1,1].grid(True)

# Show the plot
plt.tight_layout()
plt.show()
```



Save first shape (remapped based on functional map) and its reconstruction.

```
np.save('shape1_baseline.npy', v1_remapped)
np.save('shape2_reconstruction.npy',
s3.features.detach().squeeze(0).numpy())
```