

# Let's have a look at the training data that we've used to train our network

```
In [17]: # sirf functionality
from sirf.STIR import AcquisitionSensitivityModel, AcquisitionModelUsingRayTracingMatrix, ImageData, AcquisitionModel
from sirf.Utilities import examples_data_path # for our example data

# DataLoaders for Pytorch and some of the functions used
from odl_funcs.ellipses import EllipsesDataset
from odl_funcs.misc import random_phantom, affine_transform_2D_image, affine_transform_2D

# plotting
import matplotlib.pyplot as plt

# for path handling
import os

# pytorch
import torch

In [18]: # set-up redirection of STIR messages to files
msg_red = MessageRedirector('info.txt', 'warnings.txt', 'errors.txt')

# big plots
plt.rcParams['figure.dpi'] = 200

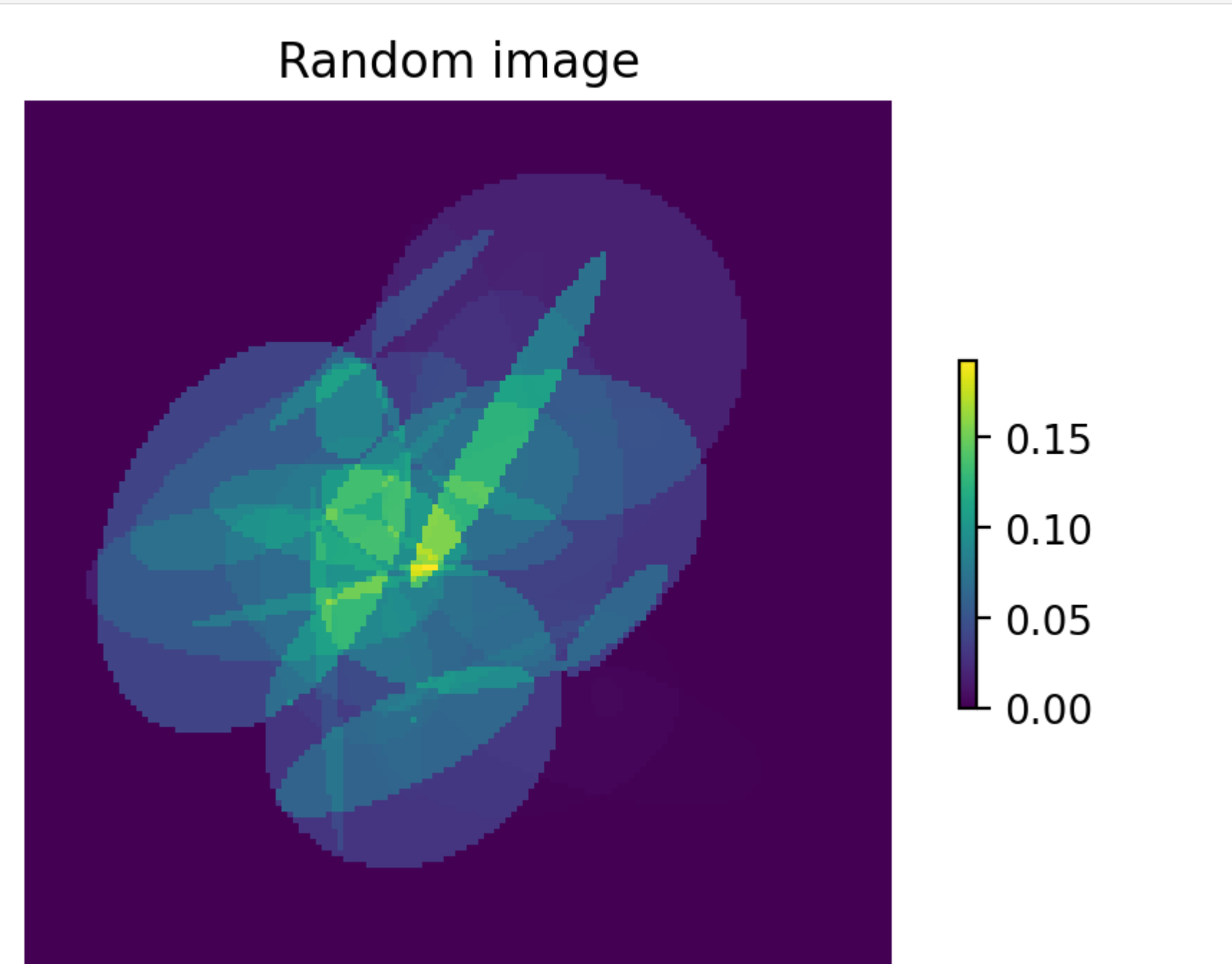
In [19]: # some handy function definitions
def plot_2d_image(idx, vol, title, clims=None, cmap="viridis"):
    """Customized version of subplot to plot 2D image"""
    plt.subplot(*idx)
    plt.imshow(vol, cmap=cmap)
    if not clims is None:
        plt.clim(clims)
    plt.colorbar(shrink=.4)
    plt.title(title)
    plt.axis("off")

random_image_array = normalise_image(random_phantom((1, 155,155), 25))*2*0.096 # this uses a pseudo-2D shape h
plot_2d_image([1,1,1], random_image_array[0], "Random image")
```

In order to simulate some random body-ish phantoms, I have decided to use random ellipses. These look something like this:

```
In [20]: def normalise_image(image):
        """Normalise image to range [0,1]"""
        image = image - image.min()
        image = image / image.max()
        return image

In [31]: random_image_array = normalise_image(random_phantom((1, 155,155), 25))*2*0.096 # this uses a pseudo-2D shape h
        plot_2d_image([1,1,1], random_image_array[0], "Random image")
```



OK so how do we train our network with this? We need to make ourselves a sensitivity image. The following is taken from the EllipsesDataset class in the odl\_funcs directory (it's been edited a bit). It takes an attenuation image and returns a sensitivity image

```
In [32]: radon_transform = AcquisitionModelUsingRayTracingMatrix()

def get_sensitivity(attenuation_image, template):
    # Forward project image then add noise
    acq_model = AcquisitionModelUsingRayTracingMatrix()
    asm_attn = AcquisitionSensitivityModel(attenuation_image, radon_transform)
    asm_attn.set_up(template)
    acq_model.set_acquisition_sensitivity(asm_attn)
    acq_model.set_up(template, attenuation_image)
    y = acq_model.backward(template.get_uniform_copy(1.0))
    return y

In order to set up our acquisition model, we need a template sinogram in order to tell sirf what kind of scanner we'll be using (e.g number of projections, voxel sizes...)
```

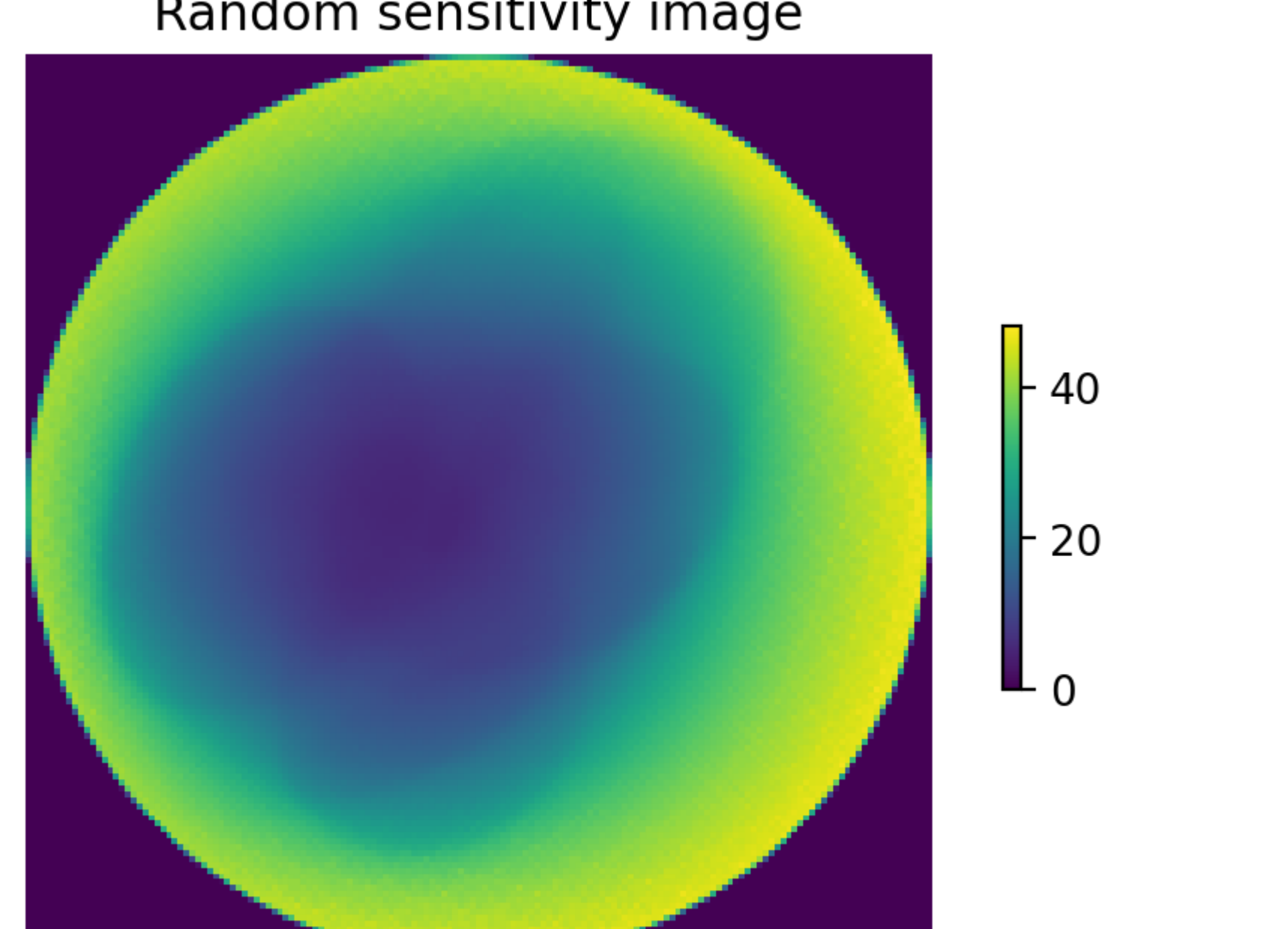
```
In [33]: data_path = os.path.join(examples_data_path('PET'), 'thorax_single_slice')
        template_sino = AcquisitionData(os.path.join(data_path, 'template_sinogram.hs'))
        template_image = ImageData(os.path.join(data_path, 'emission.hv'))

WARNING: RadioNuclideDB::get_radionuclide: unknown modality. Returning "unknown" radionuclide.
```

OK so let's now construct a SIRF ImageData Object with our random ellipse array from our template image. We'll then find the sensitivity image and plot it

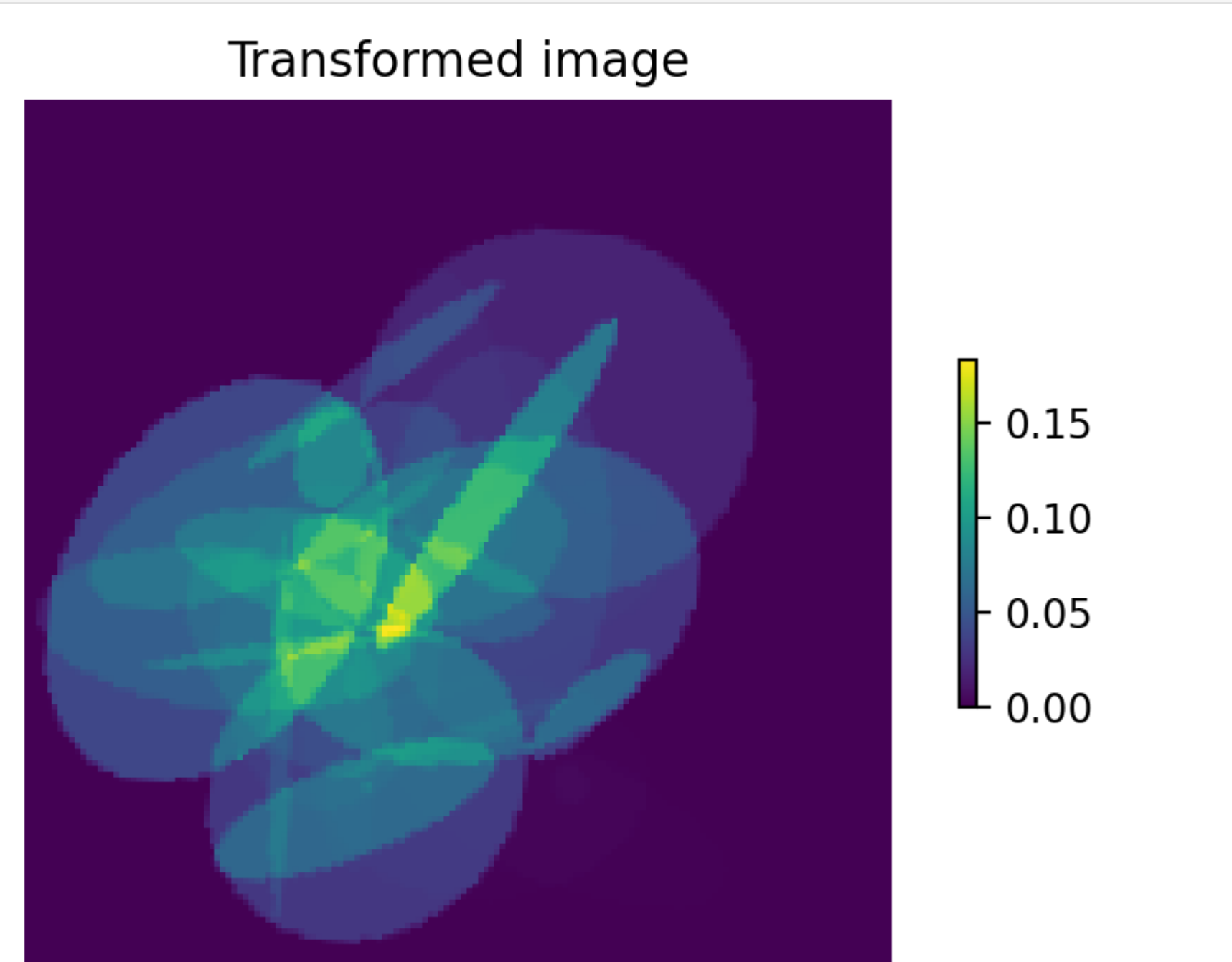
```
In [34]: random_image = template_image.fill(random_image_array)
        random_sens_image = get_sensitivity(random_image, template_sino)
        plot_2d_image([1,1,1], random_sens_image.as_array()[0], "Random sensitivity image")

applying unnormalisation...ok
backprojecting...ok
```



Right. So next we need some training data with a transformation. In order to do this we'll use an affine transformation from

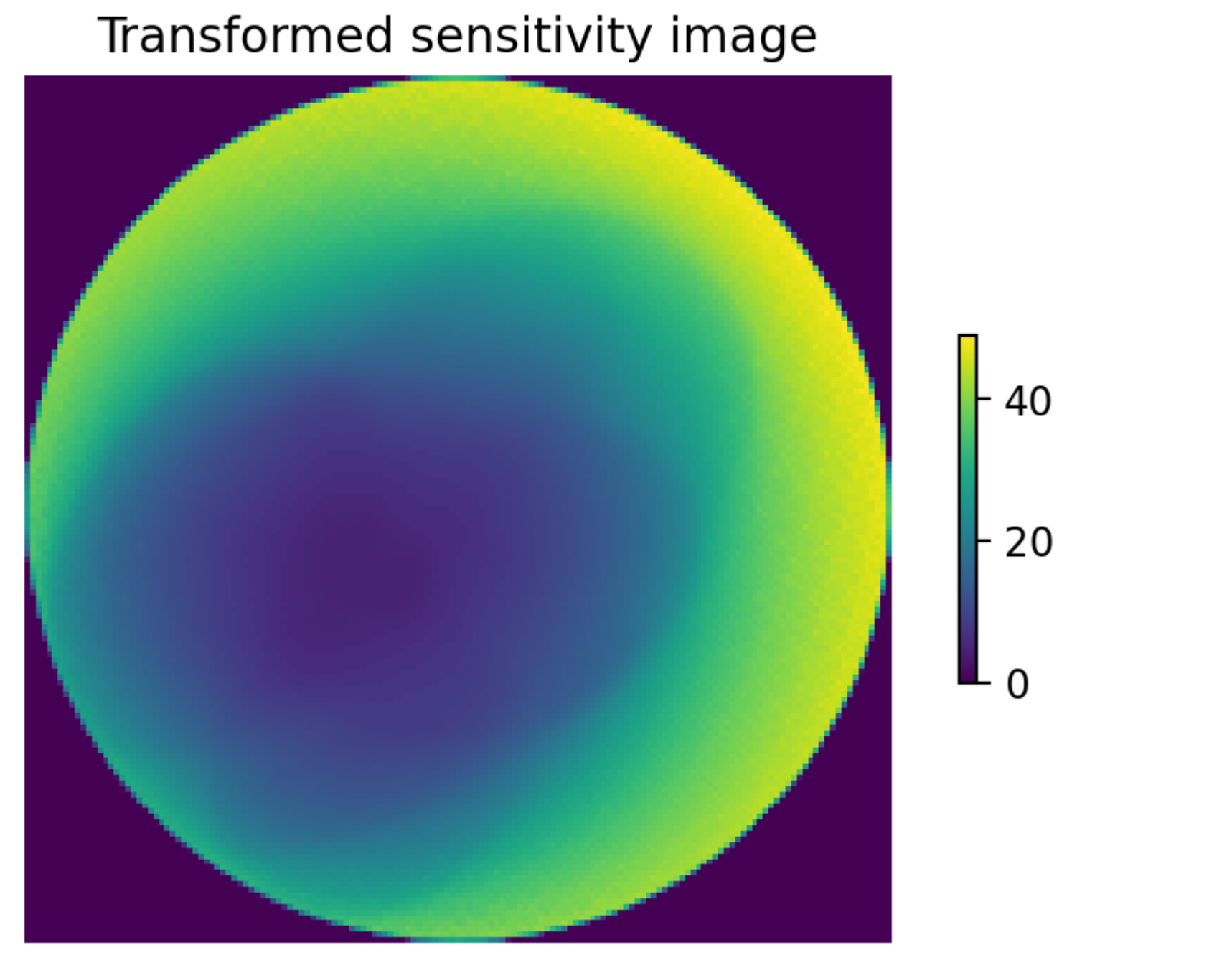
```
In [35]: # rotate, scale, translate
        theta, tx, ty, sx, sy = 0.1, 0.1, 0.1, 0.95, 0.95
        transformed_image = affine_transform_2D_image(theta, tx, ty, sx, sy, random_image)
        plot_2d_image([1,1,1], transformed_image.as_array()[0], "Transformed image")
```



And we can now find our sensitivity image to find the target data for training our model

```
In [36]: transformed_sens_image = get_sensitivity(transformed_image, template_sino)
        plot_2d_image([1,1,1], transformed_sens_image.as_array()[0], "Transformed sensitivity image")

applying unnormalisation...ok
backprojecting...ok
```

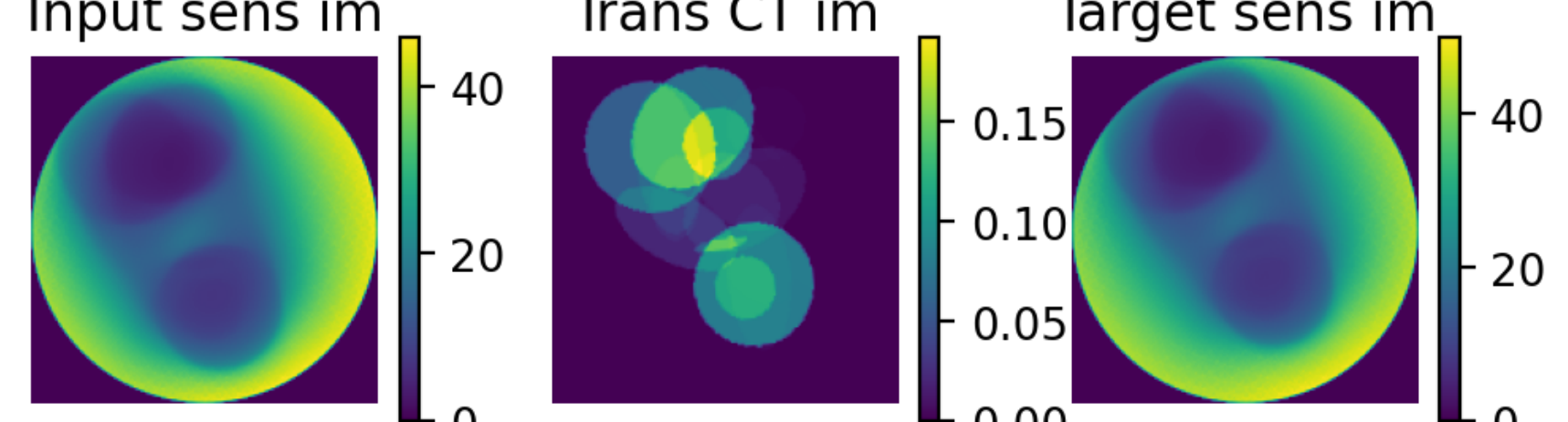


This is exactly what is happening in our Pytorch Data Loader

```
In [37]: train_dataloader = torch.utils.data.DataLoader( \
        EllipsesDataset(radon_transform, random_image, template_sino, mode="train", n_samples = 1) \
        , batch_size=1, shuffle=True)

In [38]: for data in train_dataloader: # `data` is a batch of data
        X, y = data # X is the batch of features, y is the batch of targets.
        plot_2d_image([1,3,1], X[0,0,:].numpy(), "Input sens im")
        plot_2d_image([1,3,2], X[0,1,:].numpy(), "Trans CT im")
        plot_2d_image([1,3,3], y[0,0,:].numpy(), "Target sens im")

applying unnormalisation...ok
backprojecting...ok
applying unnormalisation...ok
backprojecting...ok
```



So we input a sensitivity image and a transformed CT image and output a transformed sensitivity image

## Things to think about

- Is this the best training data (how useful is a bunch of ellipses?) - I actually have a few more functions that could be useful, but I'll let you think about this first.
- Is this the best input / output (can we use difference images? How will our model have to change?)