# Bimodal experiments

**Anders Kaestner**

**May 16, 2021**

# CONTENTS

This lecture was prepared for the neutron imaging school organized by LINX at Lund University.

CHAPTER

ONE

# BIMODAL EXPERIMENTS

```
%reload_ext autoreload
%autoreload 2
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import itertools
import numpy as np
import skimage.io as io
from scipy import linalg
import matplotlib as mpl
from sklearn import mixture
import pandas as pd

# plt.rcParams["figure.figsize"] = (8, 8)
# plt.rcParams["figure.dpi"] = 100
# plt.rcParams["font.size"] = 14
# plt.rcParams['font.family'] = ['sans-serif']
# plt.rcParams['font.sans-serif'] = ['DejaVu Sans']
# plt.style.use('default')
# sns.set_style("whitegrid", {'axes.grid': False})
```

## 1.1 Literature / Useful References

### 1.1.1 Books

#### General:

- John C. Russ, "The Image Processing Handbook",(Boca Raton, CRC Press)
- Available online within domain ethz.ch (or proxy.ethz.ch / public VPN)

### Fusion specific:

- Mitchell, H.B., "Data Fusion: Concepts and Ideas", Springer Verlag, 2012.
- Mitchel, H.B., "Image Fusion - Theories, Techniques and Applications", Springer Verlag, 2010.
- T. Stathaki, "Image fusion", Academic Press, 2008
- Goshtasby, A. Ardeshir, "Image Registration Principles, Tools and Methods", Springer Verlag, 2012
- *Xiao, G., Bavirisetti, D.P., Liu, G., Zhang, X., "Image Fusion", Springer Verlag, to be published July, 2020*

## 1.2 Outline

- Motivation (Why and How?)
- Scientific Goals
- Image fusion
- Bivariate segmentation

CHAPTER

TWO

# IMAGING MODALITIES

## 2.1 Some imaging experiments and their challenges

- Segmentation accuracy
- Estimate water content
- Segmentation accuracy
- Material classification
- Estimate water content
- Dimensional changes
- Penetration power
- Ambiguous readings

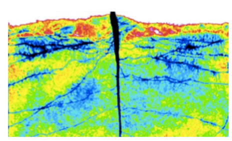


Fig. 2.1: In the soil the graylevels are often ambiguous.

## 2.2 Reasons to select an imaging modality?

Reasons to select or reject a specific imaging method

- Good transmission
- Good contrast
- Relevant features visible
- Materials can be identified
- Low transmission
- Low contrast
- Not all features visible
- Ambiguous response

Until now, we only collected image features from a single modality.

Fig. 2.2: Studies of the cultural heritage.

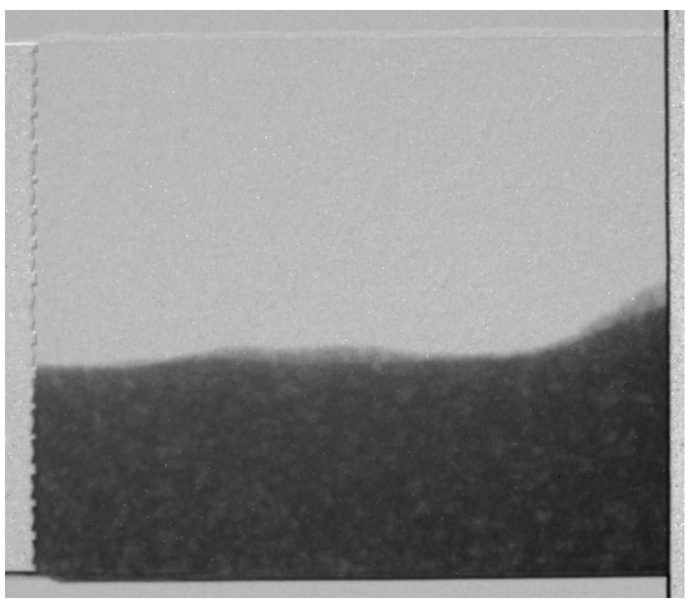


Fig. 2.3: Dimensional changes in porous media.

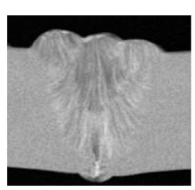


Fig. 2.4: Material science with material mixes.

## 2.3 The aim of multimodal imaging

### 2.3.1 Purpose of multi-modality

Match the advantages of each method against the disadvantages of the other methods to obtain more information than using each method individually.

1. Extend range of operation.
2. Extend spatial and temporal coverage.
3. Reduce uncertainty.
4. Increase reliability.
5. Robust system performance.

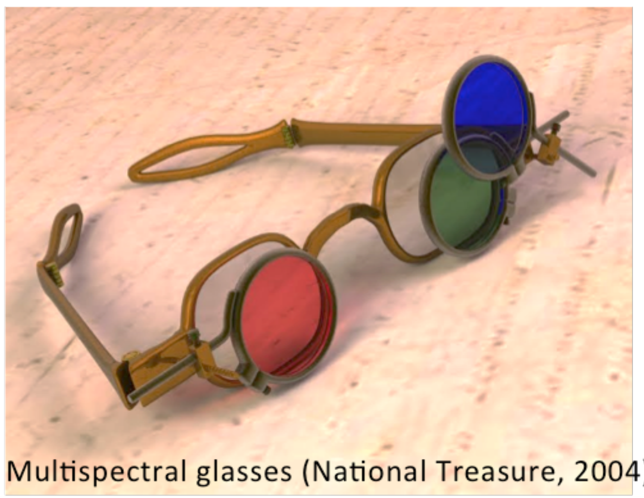



Fig. 2.5: The multispectral glasses from the movie 'National Treasure'.

## The players of an imaging experiment

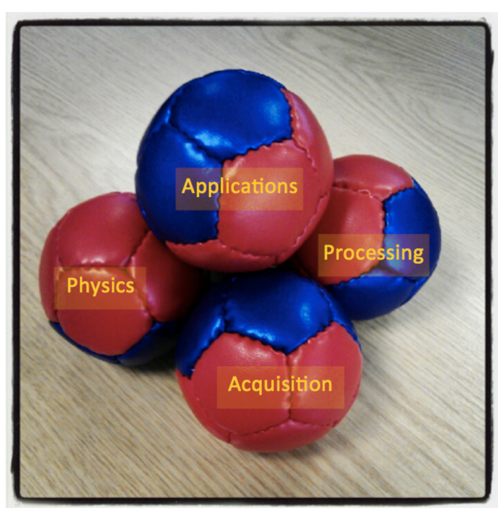



Fig. 2.6: An imaging experiment is only successful when all aspects are considered.

## 2.4 Some considered modalities - Neutrons and X-rays

In material science it often relevant to combine imagning with neutrons and X-rays. The reason is the complementarity between the two modalities. Simply put, neutrons are often sensitive to low-z materials while x-rays are more sensitive to high-z materials. Combining the two modalities is of particular interest when the sample is a mix of high and low-z materials.

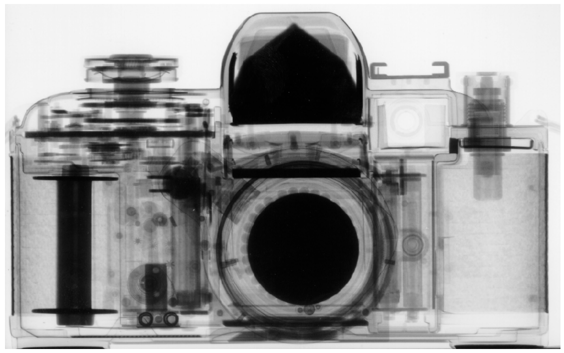


Fig. 2.7: Neutron radiography of a camera.

| Group → / ↓Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | H 3.44 | | | | | | | | | | | | | | | | | He 0.02 |
| 2 | Li 3.30 | Be 0.79 | | | | | | | | | | | B 101.6 | C 0.56 | N 0.43 | O 0.17 | F 0.20 | Ne 0.10 |
| 3 | Na 0.09 | Mg 0.15 | | | | | | | | | | | Al 0.1 | Si 0.11 | P 0.12 | S 0.06 | Cl 1.33 | Ar 0.03 |
| 4 | K 0.06 | Ca 0.08 | Sc 2.00 | Ti 0.60 | V 0.72 | Cr 0.54 | Mn 1.21 | Fe 1.19 | Co 3.92 | Ni 2.05 | Cu 1.07 | Zn 0.35 | Ga 0.49 | Ge 0.47 | As 0.67 | Se 0.73 | Br 0.24 | Kr 0.61 |
| 5 | Rb 0.08 | Sr 0.14 | Y 0.27 | Zr 0.29 | Nb 0.40 | Mo 0.52 | Tc 1.76 | Ru 0.58 | Rh 10.88 | Pd 0.78 | Ag 4.04 | Cd 115.1 | In 7.58 | Sn 0.21 | Sb 0.30 | Te 0.25 | I 0.23 | Xe 0.43 |
| 6 | Cs 0.29 | Ba 0.07 | | Hf 4.99 | Ta 1.49 | W 1.47 | Re 6.85 | Os 2.24 | Ir 30.46 | Pt 1.46 | Au 6.23 | Hg 16.21 | Tl 0.47 | Pb 0.38 | Bi 0.27 | Po - | At - | Rn - |
| 7 | Fr - | Ra 0.34 | | Rf - | Db - | Sg - | Bh - | Hs - | Mt - | Ds - | Rg - | Uub - | Uut - | Uuq - | Uup - | Uuh - | Uus - | Uuo - |
| Lanthanides | | | | La 0.52 | Ce 0.14 | Pr 0.41 | Nd 1.87 | Pm 5.72 | Sm 171.47 | Eu 94.58 | Gd 1479.0 | Tb 0.93 | Dy 32.42 | Ho 2.25 | Er 5.48 | Tm 3.53 | Yb 1.40 | Lu 2.75 |
| Actinides | | | | Ac - | Th 0.59 | Pa 8.46 | U 0.82 | Np 9.80 | Pu 50.20 | Am 2.86 | Cm - | Bk - | Cf - | Es - | Fm - | Md - | No - | Lr - |

Fig. 2.8: Attenuation coefficients for thermal neutrons.

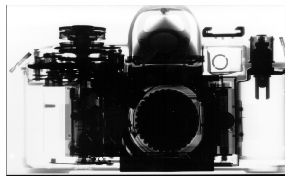


Fig. 2.9: X-ray radiography of a camera.

| Group → / ↓Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | H 0.02 | | | | | | | | | | | | | | | | | He 0.02 |
| 2 | Li 0.06 | Be 0.22 | | | | | | | | | | | B 0.28 | C 0.27 | N 0.11 | O 0.16 | F 0.14 | Ne 0.17 |
| 3 | Na 0.13 | Mg 0.24 | | | | | | | | | | | Al 0.38 | Si 0.33 | P 0.25 | S 0.30 | Cl 0.23 | Ar 0.20 |
| 4 | K 0.14 | Ca 0.26 | Sc 0.48 | Ti 0.73 | V 1.04 | Cr 1.29 | Mn 1.32 | Fe 1.57 | Co 1.78 | Ni 1.96 | Cu 1.97 | Zn 1.64 | Ga 1.42 | Ge 1.33 | As 1.50 | Se 1.23 | Br 0.90 | Kr 0.73 |
| 5 | Rb 0.47 | Sr 0.86 | Y 1.61 | Zr 2.47 | Nb 3.43 | Mo 4.29 | Tc 5.06 | Ru 5.71 | Rh 6.08 | Pd 6.13 | Ag 5.67 | Cd 4.84 | In 4.31 | Sn 3.98 | Sb 4.28 | Te 4.06 | I 3.45 | Xe 2.53 |
| 6 | Cs 1.47 | Ba 2.73 | | Hf 19.70 | Ta 25.47 | W 30.49 | Re 34.47 | Os 37.92 | Ir 39.01 | Pt 38.61 | Au 35.94 | Hg 25.88 | Tl 23.23 | Pb 22.81 | Bi 20.28 | Po 20.22 | At - | Rn 9.77 |
| 7 | Fr - | Ra 11.80 | | Rf - | Db - | Sg - | Bh - | Hs - | Mt - | Ds - | Rg - | Uub - | Uut - | Uuq - | Uup - | Uuh - | Uus - | Uuo - |
| Lanthanides | | | | La 5.04 | Ce 5.79 | Pr 6.23 | Nd 6.46 | Pm 7.33 | Sm 7.68 | Eu 5.66 | Gd 8.69 | Tb 9.46 | Dy 10.17 | Ho 10.17 | Er 11.70 | Tm 12.49 | Yb 9.32 | Lu 14.07 |
| Actinides | | | | Ac 24.47 | Th 28.95 | Pa 39.65 | U 49.08 | Np - | Pu - | Am - | Cm - | Bk - | Cf - | Es - | Fm - | Md - | No - | Lr - |

Fig. 2.10: Attenuation coefficients for 125keV X-rays.

## 2.5 Some considered modalities for medical imaging

Imaging is widely used in medical applications. There are also many different imaging modalities available, each revealing it own particular information.

The modalities also differ in the resolution that can be achived. Therefore, it makes sense to combine the modalities to increase the understanding of provided information.

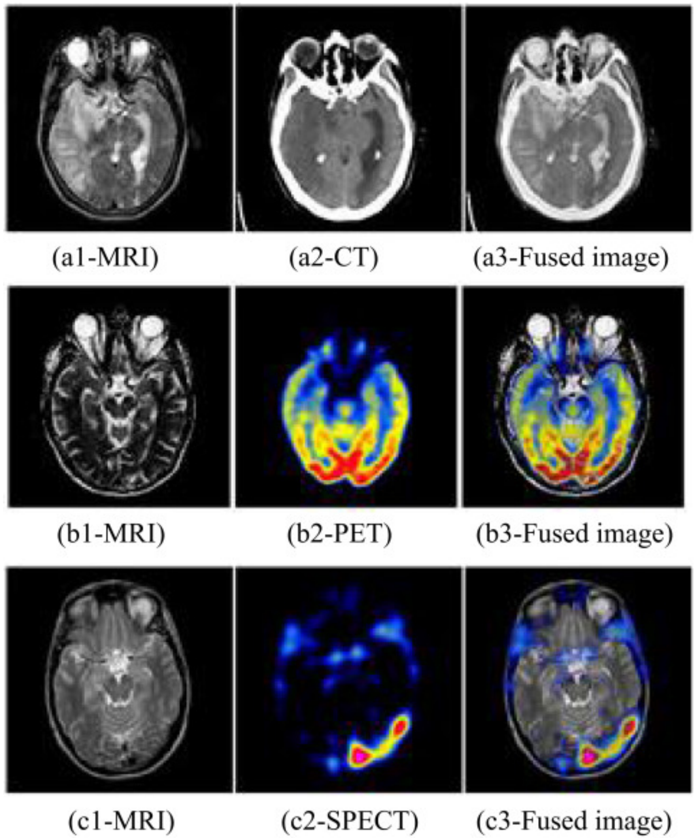



Fig. 2.11: Combining different medical imaging modalities.

Du et al. 2015

## 2.6 Some considered modalities - Grating interferometry

Grating interferometry is an imaging technique that exploits the wave property of the beam. This makes it possible to extract more information than the traditional transmission image. These are

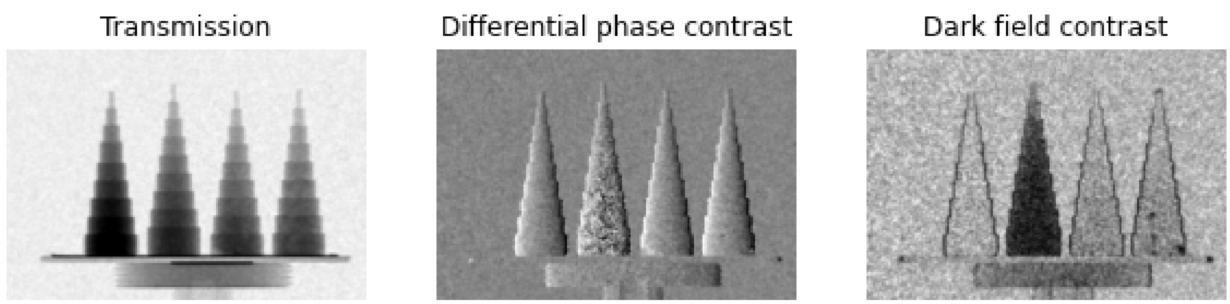
- The phase contrast - measures the phase shift of the beam to provide better contrast than the tranmission in some cases.
- The dark field contrast - is related to the scattered bream and can probe clusters of sample features that a much smaller than the resolution of the imaging system.

```
fig,ax=plt.subplots(1,3,figsize=(10,5))
ax[0].imshow(io.imread("figures/nGI_TI.png"));   ax[0].set_title('Transmission');           ax[0].axis('off')
```

(continues on next page)

(continued from previous page)

```
ax[1].imshow(io.imread("figures/nGI_DPC.png")); ax[1].set_title('Differential phase␣
↪contrast'); ax[1].axis('off')
ax[2].imshow(io.imread("figures/nGI_DFI.png")); ax[2].set_title('Dark field contrast
↪');          ax[2].axis('off');
```




- Data comparable on pixel level
- Non-linear relation between the variables.
- Improved estimation schemes using iterative process
- Physical interpretation/motivation to fuse?

## 2.7 Some considered modalities - Spectroscopic imaging

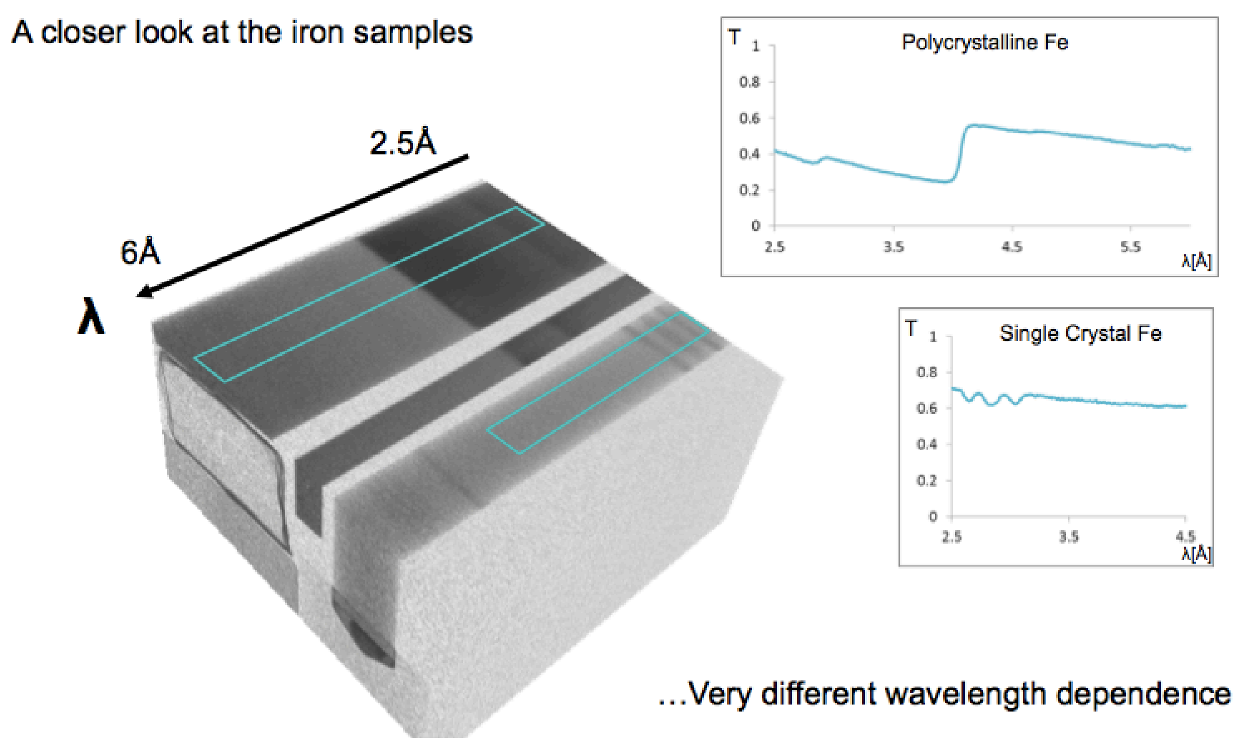



Fig. 2.12: Neutron energy scan through a piece of iron.

- Material analysis
- Selector calibration

S. Peetermans

## 2.8 Other modalities and dimensionality

**The information can also be provided as few localized points**

- Single point measurements
- Surface information
- Single radiographs vs CT data

**to provide**

- Temperature
- Flowrate
- Pressure

CHAPTER

THREE

# DATA AND IMAGE FUSION

## 3.1 Definition

The theory, techniques and tools which are used for

- combining sensor data, or data derived from sensory data,
- into a common representational format.

## 3.2 Aim

To improve the quality of the information, so that it is, in some sense, better than would be possible if the data sources were used individually.

Mitchell 2012

## 3.3 Fusion approaches - no golden recipe

### 3.3.1 Fusion strategies

- **Multivariate fusion:** All data are combined using the same concept.
- **Augmented fusion:** Modalities have different functions in the fusion process.
- **Artifact reduction by fusion:** The second modality can be used to fill in the blanks.
- **Combination:** A single fusion method may not give the final result - combination

### 3.3.2 Select strategy

The fusion strategy determined by:

- Sample composition
- Experiment objectives
- Condition of the data

## Levels of fusion

| Input | Output | Description |
|---|---|---|
| Data | Data | Input data is smoothed/filtered/segmented |
| Data | Feature | The pixels are reduced to features using multiple sources. |
| Feature | Feature | Input features are reduced in number, or new features are generated by fusing input features. |
| Feature | Decision | Input features are fused together to give output decision. |
| Decision | Decision | Multiple input decisions are fused together to give a final output decision. e.g. Random forest |

CHAPTER

FOUR

# IMAGE FUSION WORKFLOW

Image fusion is the process to combine images from different modalities with the aim to enhance the information compared the images individually. This process has serveral steps and the fusion can be done on several levels of abstraction.

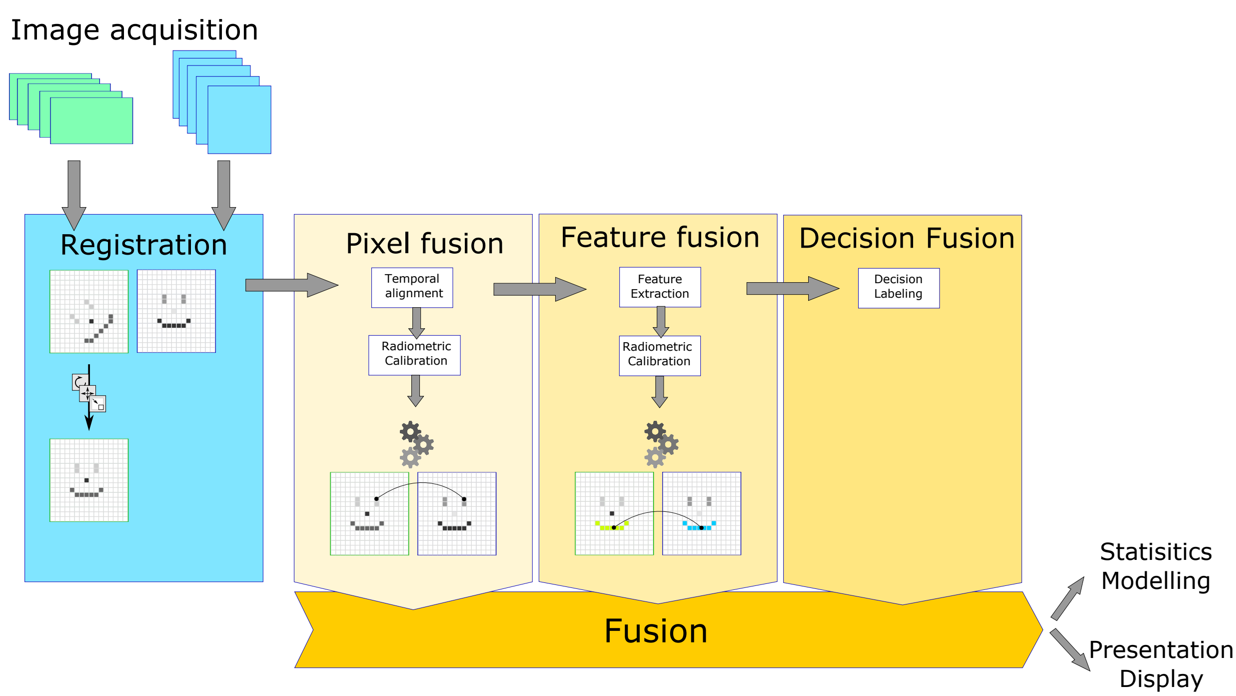



Fig. 4.1: Flow chart showing how image fusion can be done

Mitchel, 2010, Goshtasby, 2012

## 4.1 Catastrophic fusion

### 4.1.1 Definition

The combination perform worse than the individual modalities.

Catastrofic fusion can be caused by:

- Selection of the wrong variables.

- Too complex combination.
- Sensor information canceling each other.


Fig. 4.2: More chefs don't always mean better soup, the same applies to data fusion. Chose your source combination and fusion metods carefully.

## 4.2 Image registration

Image registration is a series of affine transformations to bring images on the same grid.

### 4.2.1 The process

## 4.3 Registration considerations

Registration is an optimization problem with many local minima.

### 4.3.1 Manual or guided registration

- Perform the full transformation manually
- Identify land marks, points, lines, planes
- Provide a coarse preregistration

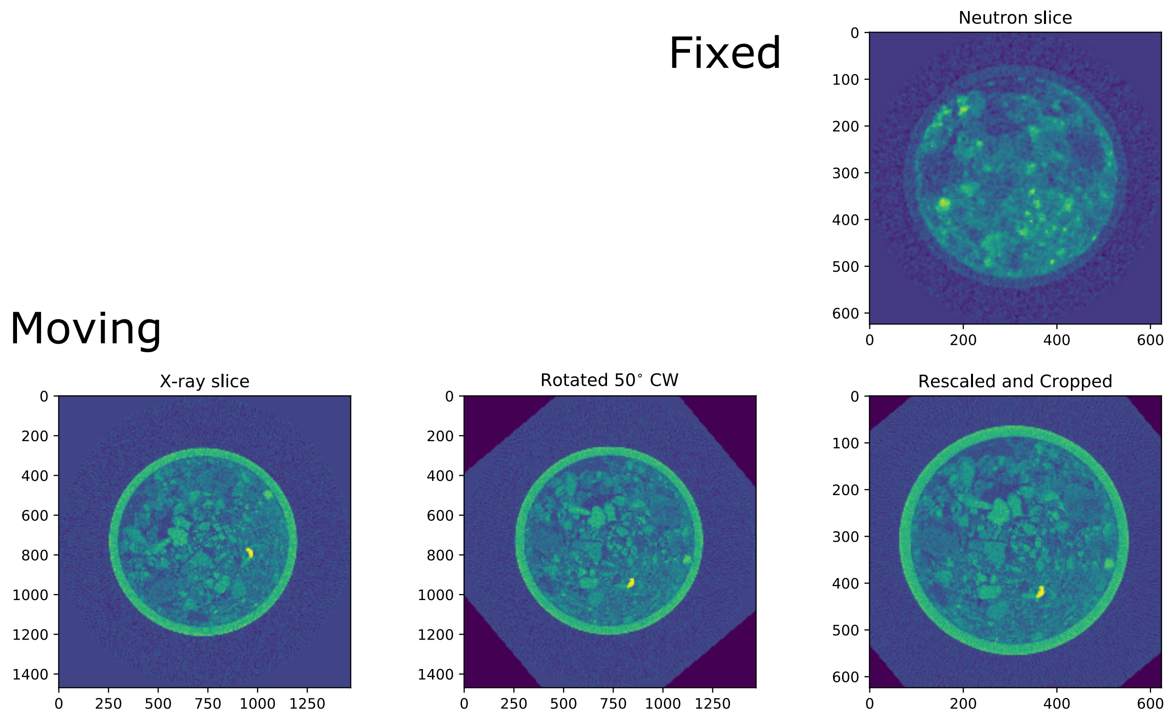



Fig. 4.3: Registration optimizes the scale, rotation, and position of an image compared to a fixed reference.

### 4.3.2 Automatic registration

- Iterative process
- Metrics
- Multi-modality loose common landmarks

Goshtasby, 2012

CHAPTER

FIVE

# QUALITATIVE FUSION: REGISTRATION AND COVISUALIZATION

Use e.g. VG Studio or 3DSlicer to

- Register data sets
- Interactive guided segmentation of the separate data sets.

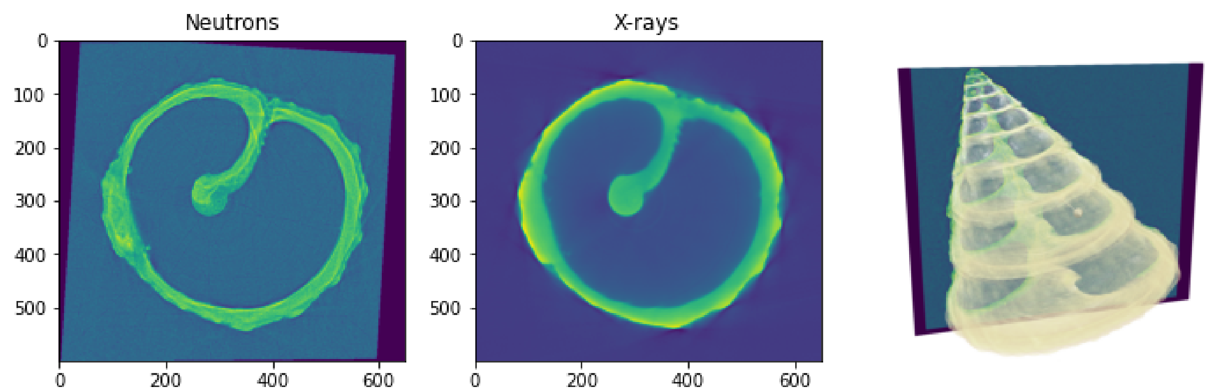
Fig. 5.1: The sword from lake Zug as seen with neutrons.

Fig. 5.2: The sword from lake Zug as seen with X-rays.

mannes2015_NXCultHer

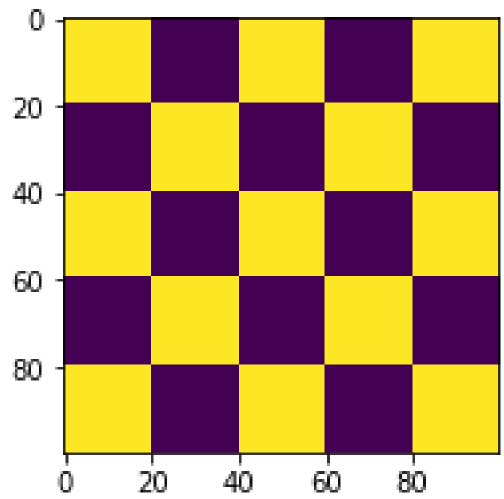
## 5.1 Let's load some test data

```
imgA=np.load('data/shellN.npy')
imgB=np.load('data/shellX.npy')
fig,(ax1,ax2,ax3) = plt.subplots(1,3,figsize=(12,5))
ax1.imshow(imgA,cmap='viridis'), ax1.set_title('Neutrons')
ax2.imshow(imgB,cmap='viridis'), ax2.set_title('X-rays');
ax3.imshow(plt.imread('figures/snailshellNeutron.png')); ax3.axis('off');
```



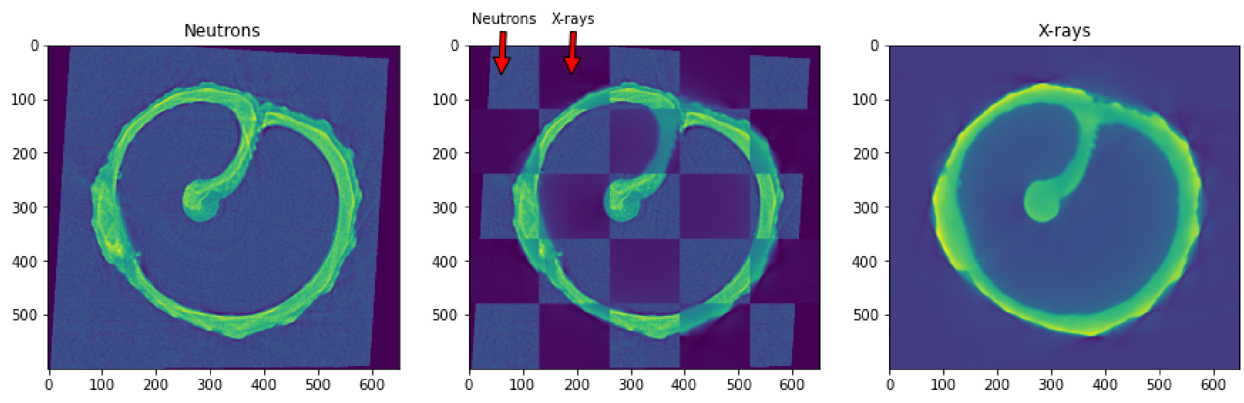

## 5.2 Visualization techniques - Checker board

```
def checkerBoard(imgA,imgB,tiles=10) :
    if imgA.shape != imgB.shape :
        raise Exception('Image have different sizes')

    dims      = imgA.shape
    tileSize = (dims[0]//tiles,dims[1]//tiles)

    mix = np.zeros(dims)

    for r in np.arange(0,tiles) :
        for c in np.arange(0,tiles) :
            if (c+r) % 2 :
                mix[(r*tileSize[0]):((r+1)*tileSize[0]),
 ↪(c*tileSize[1]):((c+1)*tileSize[1])]= imgB[(r*tileSize[0]):((r+1)*tileSize[0]),
 ↪(c*tileSize[1]):((c+1)*tileSize[1])]
            else :
                mix[(r*tileSize[0]):((r+1)*tileSize[0]),
 ↪(c*tileSize[1]):((c+1)*tileSize[1])]= imgA[(r*tileSize[0]):((r+1)*tileSize[0]),
 ↪(c*tileSize[1]):((c+1)*tileSize[1])]

    return mix
plt.figure(figsize=(3,3))
plt.imshow(checkerBoard(np.ones((100,100)),np.zeros((100,100)),tiles=5),interpolation=
 ↪'none');
```



### 5.2.1 Try checker board with images

```
fig,(ax1,ax2,ax3)=plt.subplots(1,3,figsize=(15,5))
ax1.imshow(imgA,cmap='viridis',vmin=10000,vmax=60000), ax1.set_title('Neutrons')
ax2.imshow(checkerBoard(imgA,imgB,tiles=5),cmap='viridis',vmin=10000,vmax=60000);
ax2.annotate('Neutrons',
            xy=(60, 60), xycoords='data',
            xytext=(0.1, 1.1), textcoords='axes fraction',
            arrowprops=dict(facecolor='red', shrink=0.05),
            horizontalalignment='center', verticalalignment='top')
ax2.annotate('X-rays',
            xy=(190, 60), xycoords='data',
            xytext=(0.3, 1.1), textcoords='axes fraction',
            arrowprops=dict(facecolor='red', shrink=0.05),
            horizontalalignment='center', verticalalignment='top')
ax3.imshow(imgB,cmap='viridis'), ax3.set_title('X-rays');
```



## 5.3 Visualization techniques - Color chanel mixing

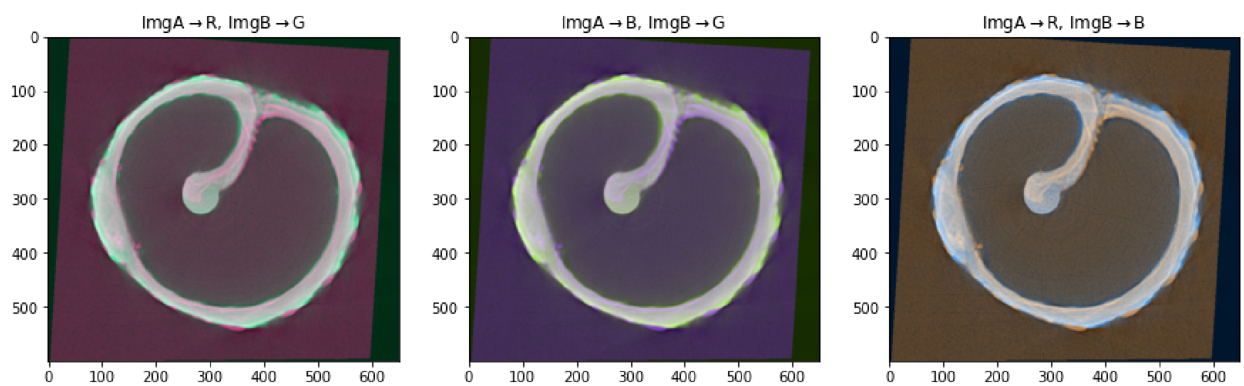
With two or more modalities, we can visualize the mix using the RGB color channels:

$$\begin{cases} R & modality_A \\ G & modality_B \\ B & \frac{modality_A + modality_B}{2} \end{cases}$$

some intensity scaling may be needed for best result.

```
def channelMix(imgA,imgB, order=(0,1,2)) :
    imgAN=(imgA-imgA.min())/(imgA.max()-imgA.min())
    imgBN=(imgB-imgB.min())/(imgB.max()-imgB.min())

    rgb=np.zeros((imgA.shape[0],imgA.shape[1],3));
    rgb[:,:,order[0]]=imgAN
    rgb[:,:,order[1]]=imgBN
    rgb[:,:,order[2]]=0.5*(imgAN+imgBN)

    return rgb
```

```
fig,(ax1,ax2,ax3)=plt.subplots(1,3,figsize=(15,6))
ax1.imshow(channelMix(imgA,imgB,order=(0,1,2))), ax1.set_title(r'ImgA$\rightarrow$R,␣
↪ImgB$\rightarrow$G');
ax2.imshow(channelMix(imgA,imgB,order=(2,1,0))), ax2.set_title(r'ImgA$\rightarrow$B,␣
↪ImgB$\rightarrow$G');
ax3.imshow(channelMix(imgA,imgB,order=(0,2,1))), ax3.set_title(r'ImgA$\rightarrow$R,␣
↪ImgB$\rightarrow$B');
```



CHAPTER

SIX

# BIMODAL SEGMENTATION

## 6.1 Histogram of single modality

When you do experiments with a single modiality, you only obtain a single histogram. The modes of the histogram may merge into a single mode if the SNR is too low to separate the feature classes. This leads to a large amount of miss-classifications. The blue region between the histogram peaks represent the area of ambiguous decisions.

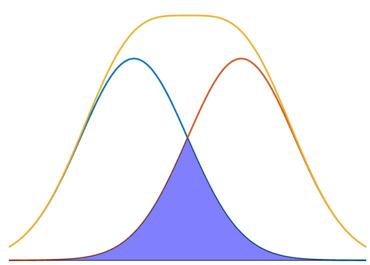


Fig. 6.1: Histogram of two classes using modality *A*.

## 6.2 Individual histograms of two modalities

Now we may conclude that the first modality we looked at doesn't provide sufficient information to make a reliable segmentation. Therefore, we go to a second modality. Unfortunately, this modality has the same low class separability as you can see in Figure 6.2. This time the two classes have different responses and the histogram modes have swapped compared to Figure 6.1.

So the conclusion is that we don't get much closer to our segmented image using these modalities individually.

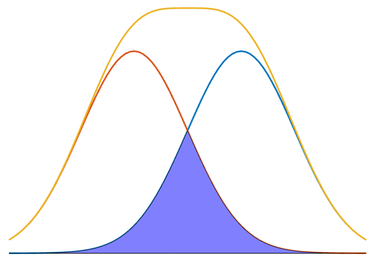


Fig. 6.2: Histogram of two classes using modality *B*.

## 6.3 Bivariate histogram

Now, if we start combining the two modalities, we start seeing the benefit of using more than one modality. The bivariate histogram, which we already have looked at in previous lectures is a great way to visualize how two variables depend on each other.

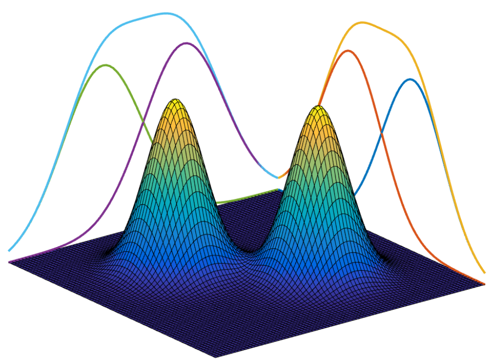


Fig. 6.3: A bivariate histogram of modalities *A* and *B*.

In the histogram show in Figure 6.3, we see that there is a clear separation between class *A* and *B* that could be easily thresholded.

### 6.3.1 Example: Roots in soil

### 6.3.2 Bivariate histogram of roots

## 6.4 Segmentation methods

### 6.4.1 Data

- Images from $M$ modalities $f_1, \dots, f_M$

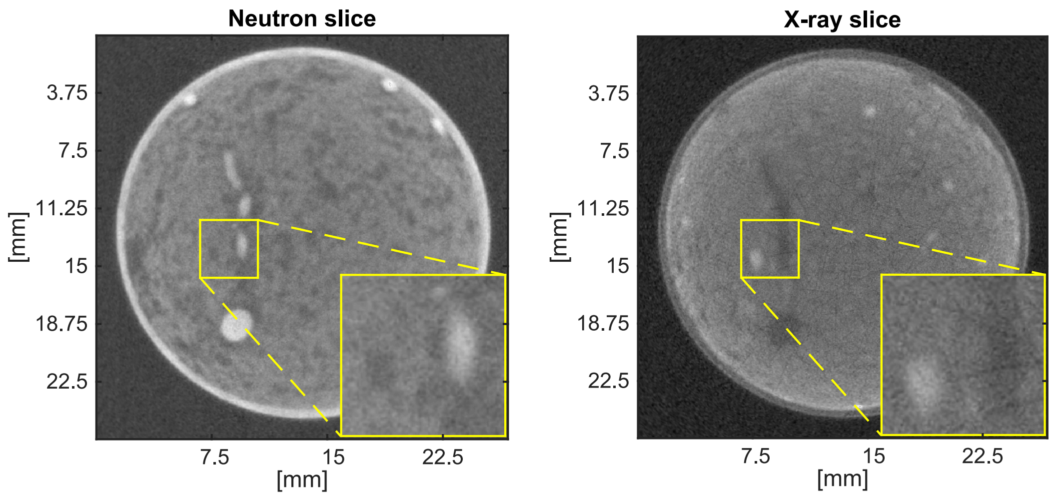



Fig. 6.4: Tomography slices of a soil sample with roots.

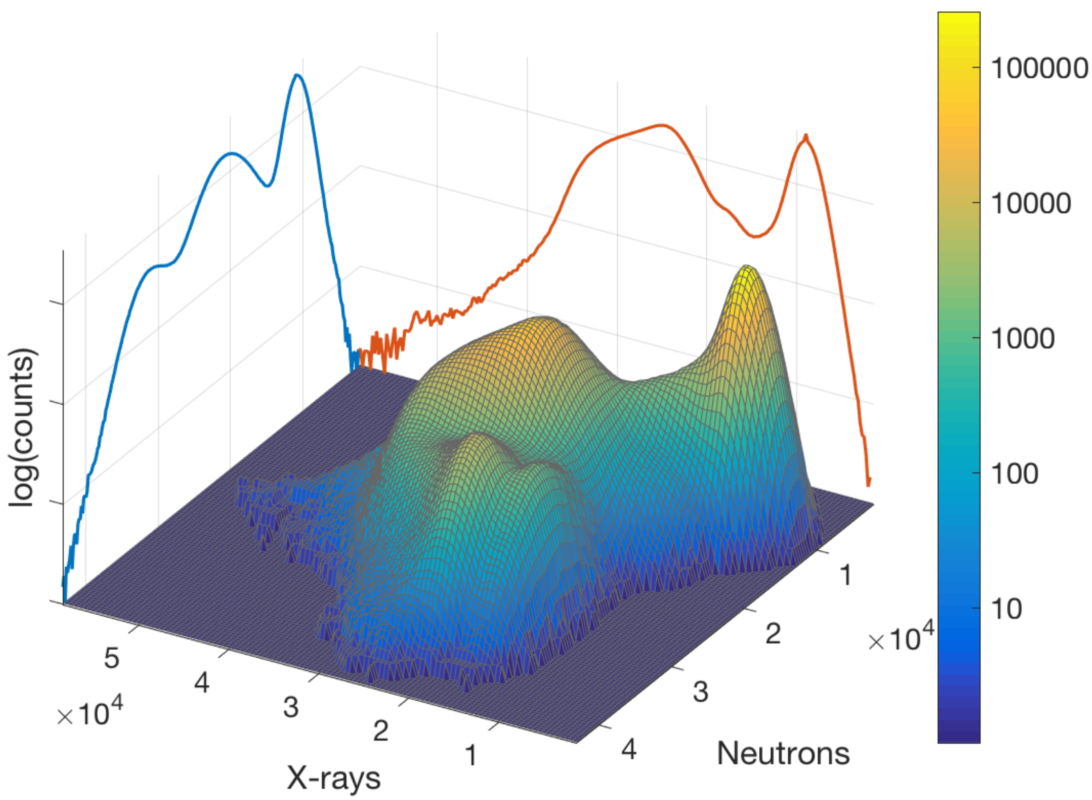



Fig. 6.5: Bivariate histogram of the root images in Figure 6.4

- Registered
- Artifact corrected

### 6.4.2 Classes

The $N$ classes are described by: $\begin{cases}\mathcal{H}_1 : p(\mu_1, \Sigma_1) \\ \mathcal{H}_2 : p(\mu_2, \Sigma_2) \\ \vdots \\ \mathcal{H}_N : p(\mu_N, \Sigma_N)\end{cases}$

Duda, Hart, and Stork, 2001

## 6.5 Previous segmentation methods

In this class we have already looked into many different ways to perform the segmentation on images. These are methods that are well suited for segmenting bi- or multivariate data:

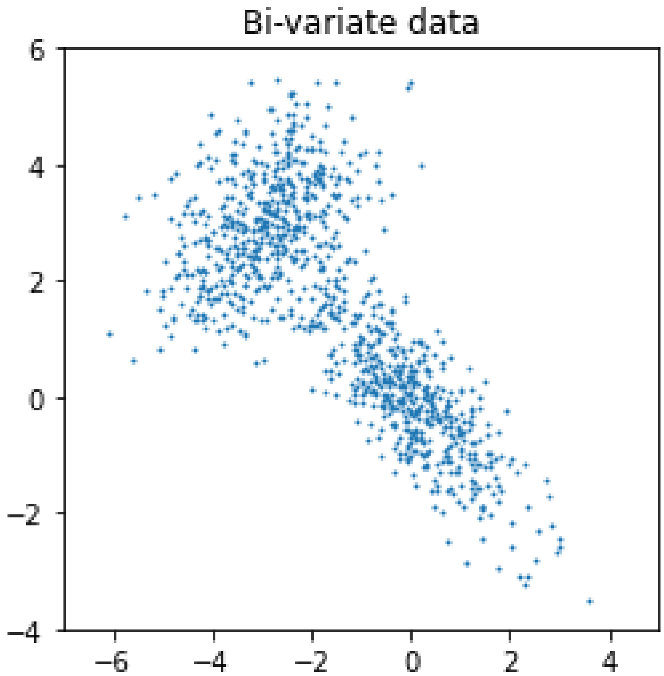
- k-means
- k-NN
- Regression
- Neural networks

## 6.6 Gaussian mixture model

With Gaussian distribution we can describe the bivariate histogram using: $p(\theta) = \sum_1^N \phi_i \, \mathcal{N}(\mu_i, \Sigma_i)$

- $\mu_i$ - vector with averages for each class.
- $\Sigma_i$ - covariance matrix for each class.
- $\phi_i$ - mixing coefficient.

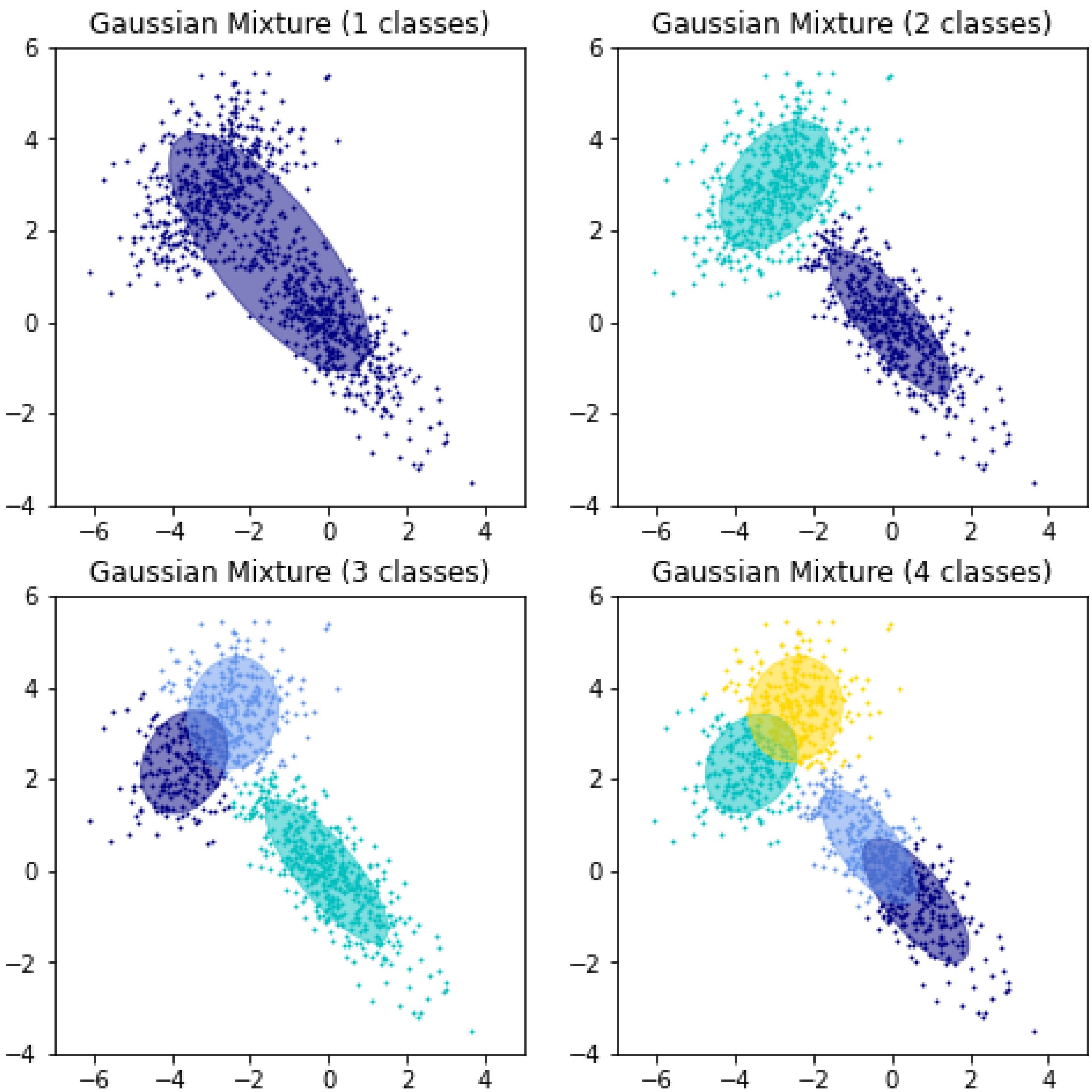
```
# Number of samples per component
n_samples = 500

# Generate random sample, two components
np.random.seed(0)
C1 = np.array([[1, -0.5], [-0.5, 1]])
C2 = np.array([[1, 0.25], [0.25, 1]])
X = np.r_[np.dot(np.random.randn(n_samples, 2), C1), np.dot(np.random.randn(n_samples,
↪ 2),C2) + np.array([-3, 3])]

plt.figure(figsize=[4,4])
plt.scatter(X[:,0],X[:,1],0.8)
plt.xlim(-7., 5.),plt.ylim(-4., 6.)
plt.title('Bi-variate data');
```




```
def plot_results(X, Y_, means, covariances, title, ax, showShape=True,␣
↪showCenter=False):
    color_iter = itertools.cycle(['navy', 'c', 'cornflowerblue', 'gold',
                                  'darkorange'])

    for i, (mean, covar, color) in enumerate(zip(
            means, covariances, color_iter)):
        v, w = linalg.eigh(covar)
        v = 2. * np.sqrt(2.) * np.sqrt(v)
        u = w[0] / linalg.norm(w[0])
        # as the DP will not use every component it has access to
        # unless it needs it, we shouldn't plot the redundant
        # components.
        if not np.any(Y_ == i):
            continue
        ax.scatter(X[Y_ == i, 0], X[Y_ == i, 1], .8, color=color)

        # Plot an ellipse to show the Gaussian component
        if showShape :
            angle = np.arctan(u[1] / u[0])
            angle = 180. * angle / np.pi  # convert to degrees
            ell = mpl.patches.Ellipse(mean, v[0], v[1], 180. + angle, color=color)
            ell.set_clip_box(ax.bbox)
            ell.set_alpha(0.5)
            ax.add_artist(ell)

        if showCenter :
            ax.plot(mean[0],mean[1],'ro')

    ax.set_xlim(-7., 5.)
    ax.set_ylim(-4., 6.)
    ax.set_title(title)
```

### 6.6.1 Gaussian mixture model fitting

```
fig, axes = plt.subplots(2,2,figsize=(8,8))
# Fit a Gaussian mixture with EM using five components
for i,ax in zip(np.arange(0,len(axes.ravel())),axes.ravel()) :
    gmm = mixture.GaussianMixture(n_components=i+1, covariance_type='full').fit(X)

    plot_results(X, gmm.predict(X), gmm.means_, gmm.covariances_,
                 title='Gaussian Mixture ({} classes)'.format(i+1), ax=ax)
```



## 6.7 Classification distances

For a set of multivariate normal distributions $p_i = \mathcal{N}(\mu_i, \Sigma_i)$

We can find the nearest neighbor class using the following distances

### 6.7.1 Euclidean

Distance between two points \$$D_E = \sqrt{(x-\mu_1)^T \cdot (x-\mu_1)}$\$

### 6.7.2 Mahanalubis

Distance from class $i$ to point $x$ \$$D_M = \sqrt{\left(x-\mu_i\right)^T \Sigma_i \left(x-\mu_i\right)}$\$

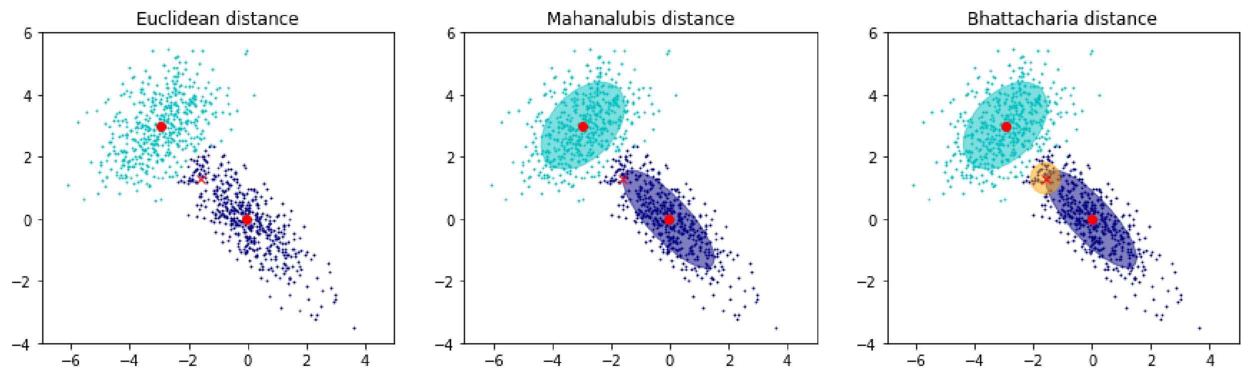
### 6.7.3 Bhattacharia

Distance between two classes \$$D_B = \frac{1}{8}\left(\mu_1-\mu_2\right)^T \Sigma \left(\mu_1-\mu_2\right) + \frac{1}{2}\ln\left(\frac{|\Sigma|}{\sqrt{|\Sigma_1|\cdot|\Sigma_2|}}\right) \qquad \Sigma = \frac{\Sigma_1+\Sigma_2}{2}$\$

Assign the point to the class with shortest distance.

## 6.8 Graphical presentation of different distances

```
gmm = mixture.GaussianMixture(n_components=2, covariance_type='full').fit(X)
m=[-1.6,1.3]
fig,(ax1,ax2,ax3)=plt.subplots(1,3,figsize=(15,4))

plot_results(X, gmm.predict(X), gmm.means_, gmm.covariances_,
             'Euclidean distance',ax1, showShape=False,showCenter=True)
ax1.plot(-1.6,1.3,'rx')
plot_results(X, gmm.predict(X), gmm.means_, gmm.covariances_,
             'Mahanalubis distance'.format(2),ax2, showCenter=True)
ax2.plot(-1.6,1.3,'rx')

plot_results(X, gmm.predict(X), gmm.means_, gmm.covariances_,
             'Bhattacharia distance'.format(2),ax3, showCenter=True)
v=1
ell = mpl.patches.Ellipse(m, v, v, 0, color='orange')
ell.set_clip_box(ax3.bbox)
ell.set_alpha(0.5)
ax3.add_artist(ell)
ax3.plot(m[0],m[1],'rx');
```




## 6.9 Segmentation by Euclidean distance

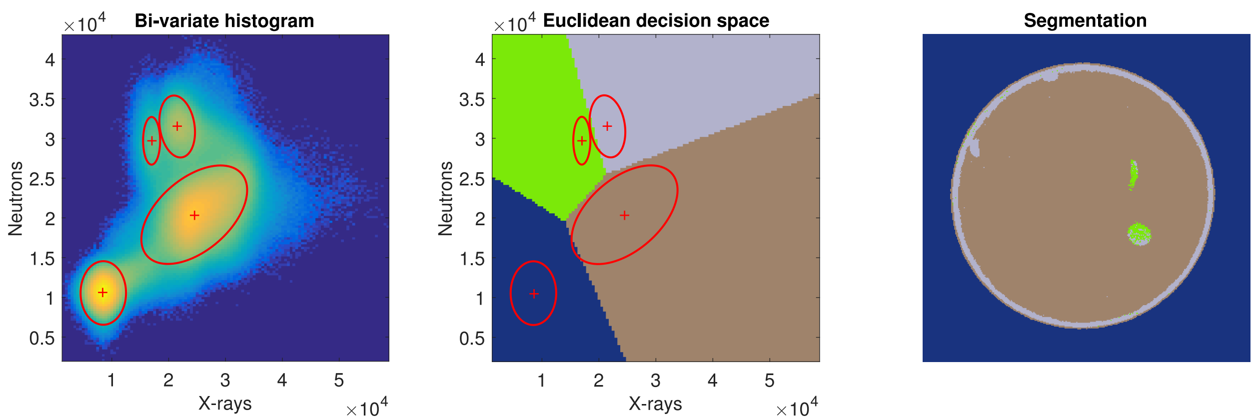



Fig. 6.6: Segmenting the root image in

kaestner2016_itmnrnx

CHAPTER

SEVEN

# BIVARIATE ESTIMATION: WORKING WITH ATTENUATION COEFFICIENTS

## 7.1 Beer-Lamberts law

$$I = I_0 \, e^{-\frac{\rho}{A} \, N_A \, \sigma \, x}$$

- $\rho$ Material denstity
- $A$ Atomic weight
- $\sigma$ microscopic cross section
  - Probability of interaction
  - modality dependent
- $x$ propagation length

## 7.2 Equation system

$$\sum_{i=1}^{N} \Sigma_i \, x_i = q_N$$
$$\sum_{i=1}^{N} \mu_i \, x_i = q_X$$

- attn coeff known $\rightarrow$ estimate lengths.
- More pixels $\rightarrow$ more materials.

# CHAPTER EIGHT

# BEYOND MULTI MODAL EXPERIMENTS

Many bimodal experiments are done separately.

There many reasons for this, two are:

- Limited resources
- Scanners at different locations

This is often the case in medical imaging where the hospitals have different dedicated machines for each modality. It is also not always that the patient is scan using all relevant modalities at the same time, but different modalities are used at different stages of the therapy.

This is also a common approach in materials science and ex situ imaging. The home laboratory may own their own X-ray CT scanner but they need to got to a large scale facility to obtain more information with further modalities.

Next steps:

- Dynamic experiments

Last week we looked into the topic of dynamic experiments. The use of bimodal imaging is also very relevant in dynamic experiments. The observed samples and processes often change shape when you introduce a liquid, apply a preasure, etc. These shape changes are often more visible in one modality than the other. Ideally, you will have a system where one modality is sensitive to dimensional changes while the other is sensity the changes in mixing ratios and other process related parameters.

- Combined setups

Combined setups all simultaneous acquisition using two modalities. This has the advantage that you can perform dynamic experiments.

Figure 6.3 show a setup for bimodal neutron and X-ray imaging. The system has two difference beam geometries neutrons uses parallel beam and X-rays a cone beam. The beams are also at oblique angles and mostly also resulting in different resolutions, there it is a first requirement that the resulting iamges are registered before any analysis can be performed.

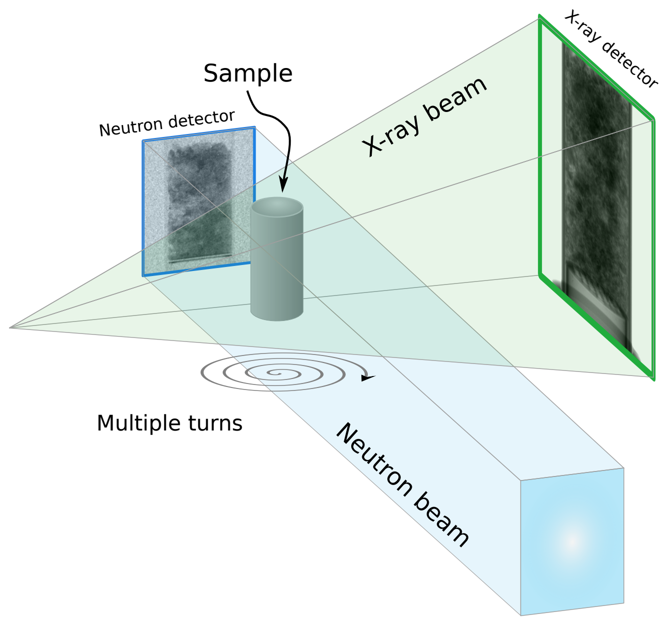



Fig. 8.1: The outline of a bimodal imaging system for neutrons and X-rays.

CHAPTER

NINE

# SUMMARY

## 9.1 Multiple modalities

- Add more information to improve the conclusions
- Add component in the analysis and visualization
- Data fusion can be done on different levels of abstraction.