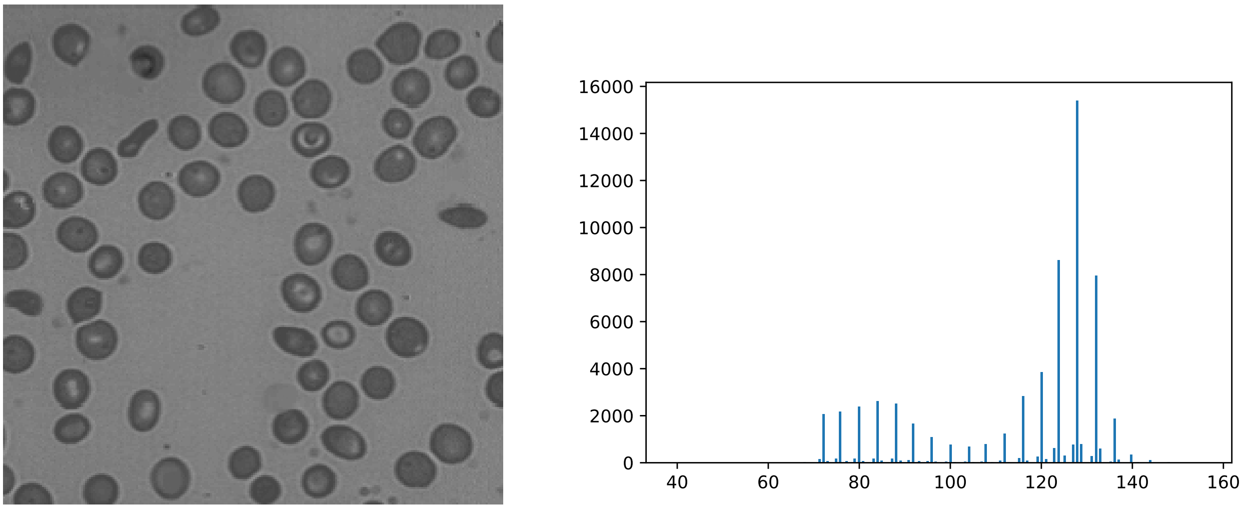
1 Python correction

1.1 Manual thresholding

1.1.1 Visual analysis of histogram

When manually choosing a threshold value, one has to analysis the histogram (Fig. 1).

```python
import numpy as np
import imageio
import matplotlib.pyplot as plt # plots
from skimage import filter # otsu thresholding

# read image
cells=imageio.imread('cells.png');

# display histogram
fig=plt.figure();
plt.hist(cells.flatten(), 256)
fig.show();
fig.savefig("histo.pdf");
```



(a) Original image.

(b) Histogram.

Figure 1: Original image and its histogram.

1.1.2 Segmentation

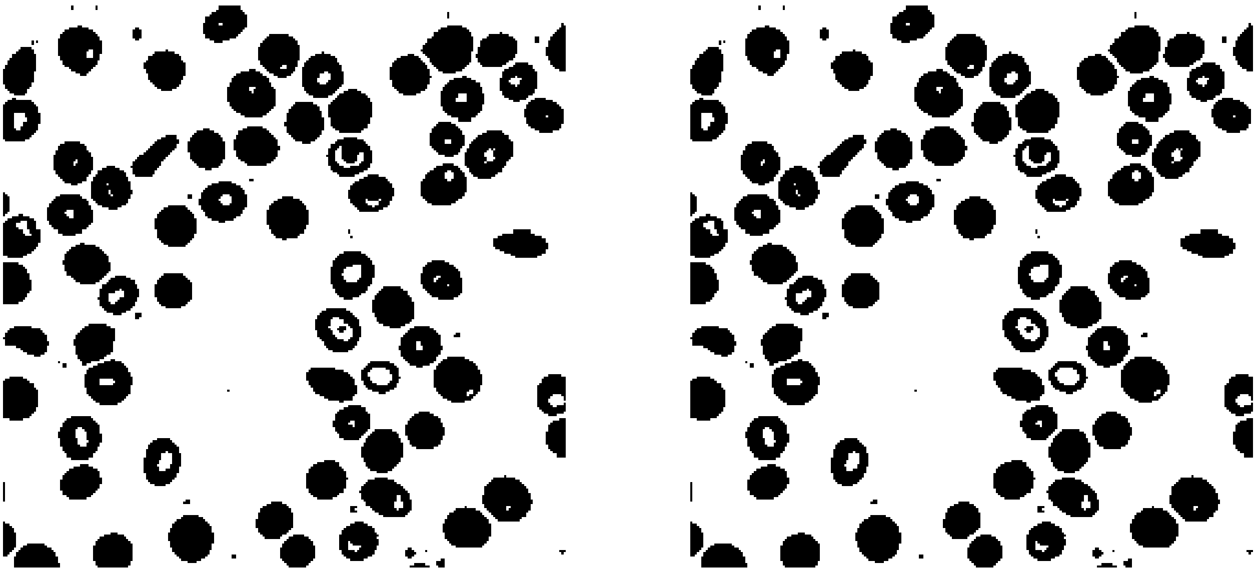
```
fig=plt.figure();
plt.subplot(1,2,1)
plt.imshow(cells, plt.cm.gray); plt.title('Original image');
plt.subplot(1,2,2)
plt.imshow(cells>80, plt.cm.gray); plt.title('Manual segmentation');
fig.savefig("manual.pdf");
```

1.2 Automatic thresholding

```
def autothresh(image):
    """ Automatic threshold method
    @param image: image to segment
    @return : threshold value
    """
    s = 0.5*(np.amin(image) + np.amax(image));
    done = False;
    while ~done:
        B = image>=s;
        sNext = .5*(np.mean(image[B]) + np.mean(image[~B]));
        done = abs(s-sNext)<.5;
        s = sNext;
    return s
```

The results are displayed using the following code (Fig. 2):

```
# Automatic threshold
s_auto= autothresh(cells);

# Otsu thresholding
s_otsu =filter.threshold_otsu(cells);

plt.figure();
plt.subplot(1,2,1)
plt.imshow(cells>s_auto, plt.cm.gray); plt.title('Automatic thresholding')
plt.subplot(1,2,2);
plt.imshow(cells>s_otsu, plt.cm.gray); plt.title('Otsu thresholding');
```



(a) Automatic threshold.

(b) Otsu threshold.

Figure 2: Automatic thresholding and thresholding by Otsu. Results are almost identical because threshold values are 105.3 and 105, respectively.

1.3 k-means clustering

Different techniques can be found in the scikit documentation. A point cloud will first be generated, from 3 clustered cloud points. The objective is then to segment all the points into their original cluster.

1.3.1 Imports

```python
import numpy as np
import matplotlib.pyplot as plt
import time

from sklearn.cluster import KMeans
```

1.3.2 Generation of point clouds

```python
def generation(n, x, y):
    Y = np.random.randn(n, 2) + np.dot(np.ones((n, 2)),
                                        np.array(((x,0), (0,y)))
                                       );
    return Y

points1=generation(100, 0, 0);
points2=generation(100, 3,4);
points3=generation(100, -5, -3);

pts=np.concatenate((points1, points2, points3));
plt.plot(pts[:,0], pts[:,1], 'ro');

plt.show();
```

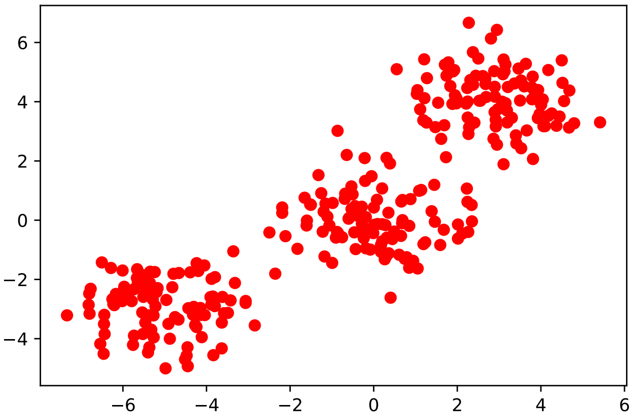


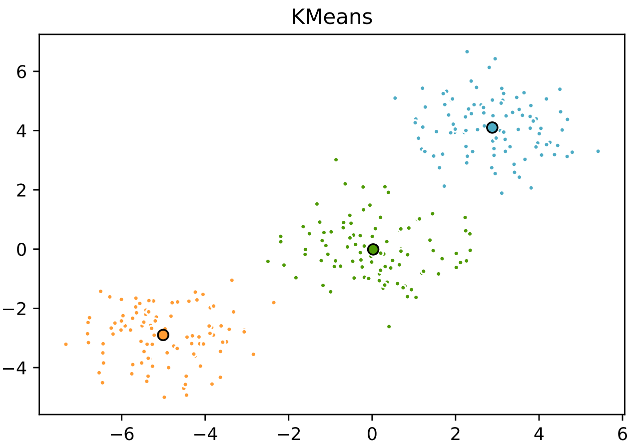
Figure 3: Point cloud.

1.3.3 *k*-means clustering

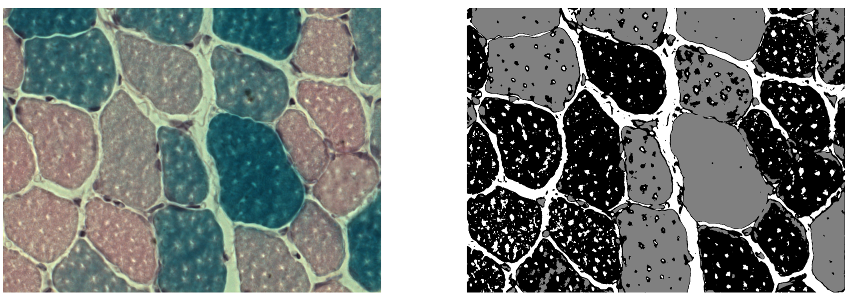
```python
n=3; # number of clusters

# k-means initialization
k_means = KMeans(init='k-means++', n_clusters=n, n_init=10)
t0 = time.time(); # computation time
k_means.fit(pts); # kmeans segmentation

t_batch = time.time() - t0;

# retrieve results
k_means_labels = k_means.labels_;
k_means_cluster_centers = k_means.cluster_centers_;

# plot
fig = plt.figure()
colors = ['#4EACC5', '#FF9C34', '#4E9A06']

# k-means
# zip agregates values two by two
for k, col in zip(range(n), colors):
    my_members = k_means_labels == k
    cluster_center = k_means_cluster_centers[k]

    # display points
    plt.plot(pts[my_members, 0], pts[my_members, 1], 'w',
             markerfacecolor=col, marker='.')

    # display centroid
    plt.plot(cluster_center[0], cluster_center[1], 'o',
              markerfacecolor=col, markeredgecolor='k',
              markersize=6)
plt.title('KMeans')
plt.show()
fig.savefig("kmeans.pdf");
```

1.4 Color image segmentation

Three different colors can be observed in the image. The objective is to separate the 3 colors with the help of the K-means algorithm. Thus, the segmentation is performed in the RGB color space, and each pixel is represented by a point in this 3D space. Initialization steps are identical to previous code. The data is converted from a color image (of size $(n, m, 3)$) to a vector (of size $(n \times m, 3)$), done by the reshape function of numpy.




```python
# load color image
cells=imageio.imread('Tv16.png');
[nLines,nCols,channels] = cells.shape
# reshape data
data = np.reshape(cells, (nLines*nCols, channels));
k_means.fit(data);

# convert result to an image
# as we got labels, we expand the dynamic (multiply by 70)
segmentation = 70*np.reshape(k_means.labels_, (nLines, nCols));

fig=plt.figure();
plt.imshow(segmentation, cmap=plt.cm.gray);
imageio.imwrite("segmentation_kmeans.png", segmentation);
```



(a) Original image.　(b) Segmented.

Figure 4: Segmentation result.

1.4.1 3D scatter plot

This is a method to display colors in the RGB cube. This method is really slow, depending on your GPU.

```python
from mpl_toolkits.mplot3d import Axes3D # 3D scatter plot

# plot
colors = ['#4EACC5', '#FF9C34', '#4E9A06']

fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

# Plot scatter points
for k, col in zip(range(n), colors):
    my_members = k_means_labels == k
    cluster_center = k_means_cluster_centers[k]
    ax.scatter(data[my_members, 0], data[my_members, 1],
               data[my_members, 2], c=col)
    ax.scatter(cluster_center[0], cluster_center[1],
               cluster_center[2], s=30, c=col)
```