Compressing images with Discrete Cosine Basis

```
In [1]: %matplotlib inline
   import numpy as np
   import scipy.fftpack
   import scipy.misc
   import matplotlib.pyplot as plt
   plt.gray()

<Figure size 432x288 with 0 Axes>

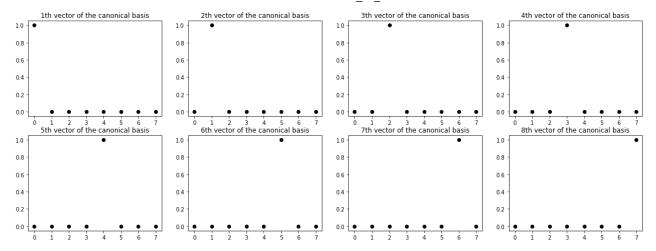
In [2]: # Two auxiliary functions that we will use. You do not need to read them (but make sure
   def dct(n):
        return scipy.fftpack.dct(np.eye(n), norm='ortho')

   def plot_vector(v, color='k'):
        plt.plot(v,linestyle='', marker='o',color=color)
```

5.3.1 The canonical basis

The vectors of the canonical basis are the columns of the identity matrix in dimension n. We plot their coordinates below for n=8.

```
In [3]:
          identity = np.identity(8)
          print(identity)
          plt.figure(figsize=(20,7))
          for i in range(8):
              plt.subplot(2,4,i+1)
              plt.title(f"{i+1}th vector of the canonical basis")
              plot_vector(identity[:,i])
          print('\n Nothing new so far...')
         [[1. 0. 0. 0. 0. 0. 0. 0.]
          [0. 1. 0. 0. 0. 0. 0. 0.]
          [0. 0. 1. 0. 0. 0. 0. 0.]
          [0. 0. 0. 1. 0. 0. 0. 0.]
          [0. 0. 0. 0. 1. 0. 0. 0.]
          [0. 0. 0. 0. 0. 1. 0. 0.]
          [0. 0. 0. 0. 0. 0. 1. 0.]
          [0. 0. 0. 0. 0. 0. 0. 1.]]
          Nothing new so far...
```



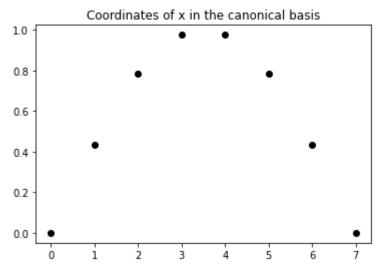
5.3.2 Discrete Cosine basis

The discrete Fourier basis is another basis of \mathbb{R}^n . The function dct(n) outputs a square matrix of dimension n whose columns are the vectors of the discrete cosine basis.

```
In [4]:
            # Discrete Cosine Transform matrix in dimension n = 8
           D8 = dct(8)
           print(np.round(D8,3))
           plt.figure(figsize=(20,7))
           for i in range(8):
                plt.subplot(2,4,i+1)
                plt.title(f"{i+1}th discrete cosine vector basis")
                plot_vector(D8[:,i])
           [[ 0.354
                      0.49
                               0.462
                                       0.416 0.354
                                                        0.278
                                                                0.191
              0.354
                      0.416
                              0.191 -0.098 -0.354 -0.49
                                                               -0.462 -0.2781
                                                                0.462
              0.354
                      0.278 -0.191 -0.49
                                              -0.354
                                                        0.098
                                                        0.416 -0.191
                      0.098 -0.462 -0.278
                                               0.354
                                                                       -0.49 ]
              0.354
              0.354 -0.098 -0.462
                                       0.278
                                               0.354 -0.416
                                                              -0.191
              0.354 -0.278 -0.191
                                       0.49
                                              -0.354 -0.098
                                                                0.462
              0.354 -0.416
                              0.191
                                                                        0.278]
                                       0.098 -0.354
                                                        0.49
                                                               -0.462
              0.354 - 0.49
                               0.462
                                      -0.416
                                               0.354 -0.278
                                                                0.191
                                                                       -0.098]]
          0.370
                                                                                           0.4
          0.365
                                                                0.2
                                      0.2
                                                                                           0.2
          0.355
                                      0.0
                                                                0.0
                                                                                           0.0
          0.350
                                                                                          -0.2
                                     -0.2
                                                                -0.2
          0.345
          0.335
                                           6th discrete cosine vector basis
           0.3
                                      0.4
                                                                                           0.4
           0.2
                                                                0.2
                                      0.2
                                                                                           0.2
           0.1
           0.0
                                      0.0
                                                                0.0
                                                                                           0.0
           -0.1
                                     -0.2
                                                                -0.2
                                                                                          -0.2
           -0.2
```

5.3 (a) Check numerically (in one line of code) that the columns of D8 are an orthonormal basis of \mathbb{R}^8 (ie verify that the Haar wavelet basis is an orthonormal basis).

```
print(np.round(D8.T @ D8),2)
In [5]:
         [[ 1. -0.
                    0. -0.
                            0. -0. -0.
          [-0. 1. -0. 0. -0. -0. -0.
                            0. -0.
          [ 0. -0.
                    1. -0.
                  -0.
                        1. -0.
                    0. -0.
                            1. -0. -0. -0.]
          [ 0. -0.
          [-0. -0. -0.
                       0. -0.
                                1.
          [-0. -0.
                    0. -0. -0.
                                0.
               0. -0. -0. -0. -0.
In [6]:
          # Let consider the following vector x
          x = np.sin(np.linspace(0,np.pi,8))
          plt.title('Coordinates of x in the canonical basis')
          plot vector(x)
```



5.3 (b) Compute the vector $v \in \mathbb{R}^8$ of DCT coefficients of x. (1 line of code!), and plot them.

How can we obtain back x from v? (1 line of code!).

```
In [7]:
           v = D8.T @ x
          plot_vector(v)
          x = D8 @ v
          print(np.round(x,2))
                0.43 0.78 0.97 0.97 0.78 0.43 0.
          [0.
           1.5
           1.0
           0.5
           0.0
          -0.5
          -1.0
                                                  5
```

6

0

1

3

5.3.3 Image compression

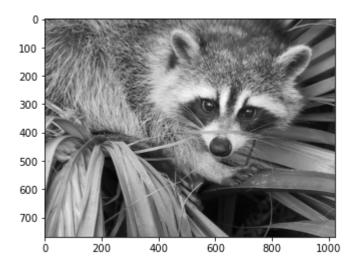
In this section, we will use DCT modes to compress images. Let's use one of the template images of python.

```
image = scipy.misc.face(gray=True)
h,w = image.shape
print(f'Height: {h}, Width: {w}')

plt.imshow(image)
```

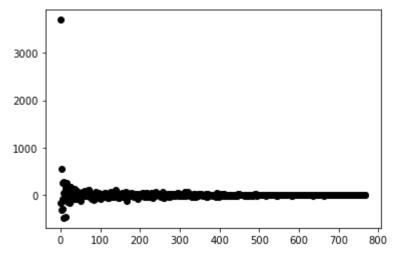
Height: 768, Width: 1024

Out[8]: <matplotlib.image.AxesImage at 0x1d762d404c0>



5.3 (c) We will see each column of pixels as a vector in \mathbb{R}^{768} , and compute their coordinates in the DCT basis of \mathbb{R}^{768} . Plot the entries of x , the first column of our image.

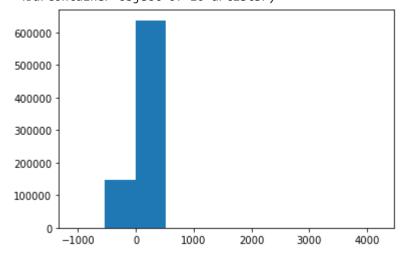
```
In [9]:
    D768 = dct(768)
    transformed = D768.T @ image
    x = transformed[:,0]
    plot_vector(x)
```



5.3 (d) Compute the 768 x 1024 matrix dct_coeffs whose columns are the dct coefficients of the columns of image . Plot an histogram of there intensities using plt.hist .

```
In [13]:
    dct_coeffs = transformed
    plt.hist(dct_coeffs.flatten())
```

```
Out[13]: (array([6.36000e+02, 1.47189e+05, 6.37024e+05, 5.19000e+02, 4.00000e+01, 0.00000e+00, 2.67000e+02, 2.41000e+02, 2.69000e+02, 2.47000e+02]), array([-1064.43123878, -537.21884715, -10.00645553, 517.20593609, 1044.41832772, 1571.63071934, 2098.84311097, 2626.05550259, 3153.26789421, 3680.48028584, 4207.69267746]), <BarContainer object of 10 artists>)
```



Since a large fraction of the dct coefficients seems to be negligible, we see that the vector \mathbf{x} can be well approximated by a linear combination of a small number of discrete cosines vectors.

Hence, we can 'compress' the image by only storing a few dct coefficients of largest magnitude.

Let's say that we want to reduce the size by 98%: Store only the top 2% largest (in absolute value) coefficients of wavelet_coeffs .

5.3 (e) Compute a matrix thres_coeffs who is the matrix dct_coeffs where about 97% smallest entries have been put to 0.

```
dct_coeffs[abs(dct_coeffs) < np.quantile(dct_coeffs, .97)] = 0
thres_coeffs = dct_coeffs</pre>
```

5.3 (f) Compute and plot the <code>compressed_image</code> corresponding to <code>thres_coeffs</code> .

```
compressed_image = D768 @ thres_coeffs
plt.imshow(compressed_image)
```

Out[20]: <matplotlib.image.AxesImage at 0x1d7625c9430>



In []:		
In []:		