Computer Vision (CSE-6239)

Programming Assignment

Interest Point Matching And Find Homography Matrix

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1. Find corners (at least 20)using Harris corner detector from two different images

1. Show the found corneron the images

2. Use SIFT like or MOPS (Multiscale Oriented Patches) descriptor

1. Present a graphical representation of the descriptors

3. Find matches among the key points using different (Euclidian, cosine similarity, correlation, SSD,Nearest neighbor ratio)

1. Show the matching pair in a side-by-side image

4. Manually/Automatically chose at least four matching pairand represent and show them as Ah=0 form, where h is projective transformation / homographyparameters.

5. Find homography matrix H by solving the Eqn Ah=0 using the technique of solving Homogeneous linear system or Homogeneous least square linear system.

1. Explain the method of solving in the report as well as the solution.

6. Apply H to transformfirst image into a homographictransformed versionusing backward warping, also show all the images (first, 2nd, and the homographic transformed)side-by-side.Also showthe difference between 2nd and transformedimages

In [76]:

```
import numpy as np
import matplotlib.pyplot as plt
import cv2
import matplotlib.image as mpimg
from skimage.color import rgb2gray
from scipy import ndimage
from pylab import *
from numpy import *
import sys
import random
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:

```
# Read images
img1 = cv2.imread('NotreDame1.jpg')
img2 = cv2.imread('NotreDame2.jpg')
# RGB to GRAY CONVERT
gray_img1 = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)
gray_img2 = cv2.cvtColor(img2, cv2.COLOR_BGR2GRAY)
```

1. Find corners (at least 20) using Harris corner detector from two different images

In [3]:

```
# Define Harris Corner Detection Function

def findHarrisCorner(image, window_size = 5, k = 0.04, thres = 10000):
```

```
    # Find image gardient

    # Sobel X and Y derivatives
    dx = cv2.Sobel(image,cv2.CV_64F,1,0,ksize=5)
    dy = cv2.Sobel(image,cv2.CV_64F,0,1,ksize=5)

    # Products of derivatives
    Ixx = dx**2
    Iyy = dy**2
    Ixy = dx * dy

    height = image.shape[0] # image height
    width = image.shape[1] # image width

    newImg = image.copy()

    color_img = cv2.cvtColor(newImg, cv2.COLOR_GRAY2RGB) # Gray to RGB convert
    offset = int(window_size / 2)

    #loop over through image and find corners
    for y in range(offset, height-offset):
            for x in range(offset, width-offset):

                # Shift Intensity
                windowIxx = Ixx[y - offset:y + offset + 1, x - offset:x + offset + 1]
                windowIxy = Ixy[y - offset:y + offset + 1, x - offset:x + offset + 1]
                windowIyy = Iyy[y - offset:y + offset + 1, x - offset:x + offset + 1]

                # Calculate sum of square
                Sxx = windowIxx.sum()
                Syy = windowIyy.sum()
                Sxy = windowIxy.sum()

                # Find determinant and trace that use to get corners
                det = (Sxx * Syy) - (Sxy**2)
                trace = Sxx + Syy

                # Response score
                R = det - k * (trace**2)
                #print('r', R)

                #If corner response is over threshold then color(Red) the point location
                if R > thres:
                    color_img.itemset((y, x, 0), 255)
                    color_img.itemset((y, x, 1), 0)
                    color_img.itemset((y, x, 2), 0)
    return color_img
```

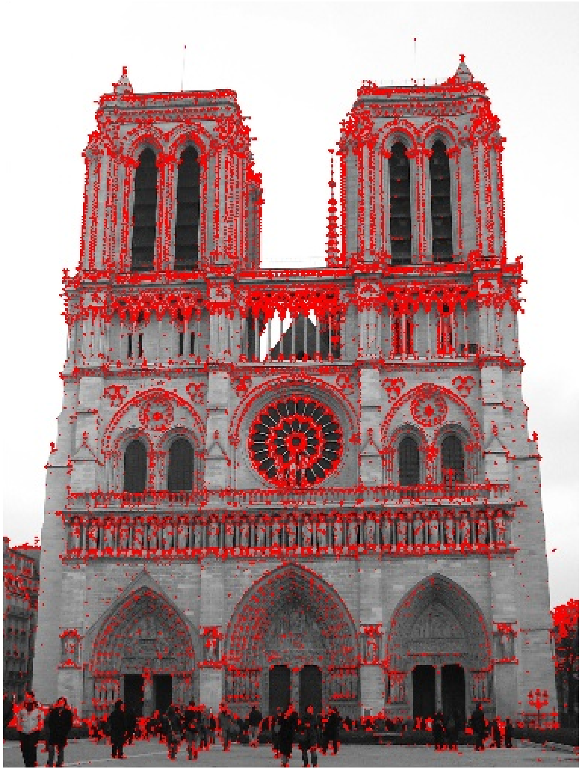
In [66]:

```
# Compute Harris corners of image 1
harris_corners_img1 = findHarrisCorner(gray_img1, 3, 0.01, 10000000000000) # image , window_size ,
k, threshold
harris_corners_img1 = np.int0(harris_corners_img1)
# Compute Harris corners of image 2
harris_corners_img2 = findHarrisCorner(gray_img2, 3, 0.01, 10000000000000) # image , window_size ,
k, threshold
harris_corners_img2 = np.int0(harris_corners_img2)

# Visualization
fig, ax=plt.subplots(2, 2, figsize = (15,15))

ax[0,0].imshow(cv2.cvtColor(img1, cv2.COLOR_BGR2RGB))
ax[0,0].set_title('NoterDame1')
ax[0,0].axis('off')

ax[0,1].imshow(harris_corners_img1)
ax[0,1].set_title('HC with window=3*3, K=0.04 and t=10^13')
ax[0,1].axis('off')

ax[1,0].imshow(cv2.cvtColor(img2, cv2.COLOR_BGR2RGB))
ax[1,0].set_title('NoterDame2')
ax[1,0].axis('off')

ax[1,1].imshow(harris_corners_img2)
```

```
ax[1,1].set_title('HC with window=3*3, K=0.04 and t=10^13')
ax[1,1].axis('off')

plt.tight_layout()
plt.show()
```

NoterDame1

HC with window=3*3, K=0.04 and t=10^13



NoterDame2

HC with window=3*3, K=0.04 and t=10^13

2. Use SIFT like or MOPS (Multiscale Oriented Patches) descriptor

Scale Invariant Feature Transform, is a method for extracting feature vectors that describe local patches of an image.

Steps of SIFT Algorithm Implementation

1. Scale-Space Extrema Detection

2. Keypoint Localization
3. Orientation Assignment
4. Local Descriptor Creation

Scale-Space Extrema Detection

In [82]:

```
# Gaussian filter
def gaussian_filter(sigma):
    size = 2*np.ceil(3*sigma)+1
    x, y = np.mgrid[-size//2 + 1:size//2 + 1, -size//2 + 1:size//2 + 1]
    g = np.exp(-((x**2 + y**2)/(2.0*sigma**2))) / (2*np.pi*sigma**2)
    return g/g.sum()
```

In [81]:

```
# Generate a Gaussian octave
def generate_octave(init_level, s, sigma):
    octave = [init_level]

    k = 2**(1/s)
    kernel = gaussian_filter(k * sigma)

    for i in range(s+2):
        next_level = convolve(octave[-1], kernel)
        octave.append(next_level)

    return octave
# Generate the whole Gaussian pyramid
def generate_gaussian_pyramid(im, num_octave, s, sigma):
    pyr = []

    for _ in range(num_octave):
        octave = generate_octave(im, s, sigma)
        pyr.append(octave)
        im = octave[-3][::2, ::2]

    return pyr
```

In [80]:

```
# Create the DoG pyramid
def generate_DoG_octave(gaussian_octave):
    octave = []

    for i in range(1, len(gaussian_octave)):
        octave.append(gaussian_octave[i] - gaussian_octave[i-1])

    return np.concatenate([o[:,:,np.newaxis] for o in octave], axis=2)

def generate_DoG_pyramid(gaussian_pyramid):
    pyr = []

    for gaussian_octave in gaussian_pyramid:
        pyr.append(generate_DoG_octave(gaussian_octave))

    return pyr
```

Extrema Detection

In [79]:

```
# Get initial candidate keypoints from given DoG octave
def get_candidate_keypoints(D, w=16):
    candidates = []

    ''' Start '''
    # These 2 lines aren't specified in the paper but it makes it so the extrema
    # are found within the entire octave. They are always found in the first or
    # last layer so I probably have something wrong with my DoG pyramid construction.
    D[:,:,0] = 0
```

```
    D[:,:,0] = 0
    D[:,:,-1] = 0
    ''' End '''

    # have to start at w//2 so that when getting the local w x w descriptor, we don't fall off
    for i in range(w//2+1, D.shape[0]-w//2-1):
        for j in range(w//2+1, D.shape[1]-w//2-1):
            for k in range(1, D.shape[2]-1):
                patch = D[i-1:i+2, j-1:j+2, k-1:k+2]
                if np.argmax(patch) == 13 or np.argmin(patch) == 13:
                    candidates.append([i, j, k])

    return candidates
# Keypoint Localization
def localize_keypoint(D, x, y, s):
    dx = (D[y,x+1,s]-D[y,x-1,s])/2.
    dy = (D[y+1,x,s]-D[y-1,x,s])/2.
    ds = (D[y,x,s+1]-D[y,x,s-1])/2.

    dxx = D[y,x+1,s]-2*D[y,x,s]+D[y,x-1,s]
    dxy = ((D[y+1,x+1,s]-D[y+1,x-1,s]) - (D[y-1,x+1,s]-D[y-1,x-1,s]))/4.
    dxs = ((D[y,x+1,s+1]-D[y,x-1,s+1]) - (D[y,x+1,s-1]-D[y,x-1,s-1]))/4.
    dyy = D[y+1,x,s]-2*D[y,x,s]+D[y-1,x,s]
    dys = ((D[y+1,x,s+1]-D[y-1,x,s+1]) - (D[y+1,x,s-1]-D[y-1,x,s-1]))/4.
    dss = D[y,x,s+1]-2*D[y,x,s]+D[y,x,s-1]

    J = np.array([dx, dy, ds])
    HD = np.array([
        [dxx, dxy, dxs],
        [dxy, dyy, dys],
        [dxs, dys, dss]])

    offset = -LA.inv(HD).dot(J) # I know you're supposed to do something when an offset dimension i
s >0.5 but I couldn't get anything to work.
    return offset, J, HD[:2,:2], x, y, s

def find_keypoints_for_DoG_octave(D, R_th, t_c, w):
    candidates = get_candidate_keypoints(D, w)
    #print('%d candidate keypoints found' % len(candidates))

    keypoints = []

    for i, cand in enumerate(candidates):
        y, x, s = cand[0], cand[1], cand[2]
        offset, J, H, x, y, s = localize_keypoint(D, x, y, s)

        contrast = D[y,x,s] + .5*J.dot(offset)
        if abs(contrast) < t_c: continue

        w, v = LA.eig(H)
        r = w[1]/w[0]
        R = (r+1)**2 / r
        if R > R_th: continue

        kp = np.array([x, y, s]) + offset
        if kp[1] >= D.shape[0] or kp[0] >= D.shape[1]: continue # throw out boundary points because
I don't want to deal with them

        keypoints.append(kp)

    #print('%d keypoints found' % len(keypoints))
    return np.array(keypoints)
# Calculate the keypoints for the whole DoG pyramid
def get_keypoints(DoG_pyr, R_th, t_c, w):
    kps = []

    for D in DoG_pyr:
        kps.append(find_keypoints_for_DoG_octave(D, R_th, t_c, w))

    return kps
```

Orientation Assignment

In [78]:

```
# Getting the gradient in polar coordinates
```

```python
# Getting the gradient in polar coordinates
def cart_to_polar_grad(dx, dy):
    m = np.sqrt(dx**2 + dy**2)
    theta = (np.arctan2(dy, dx)+np.pi) * 180/np.pi
    return m, theta

def get_grad(L, x, y):
    dy = L[min(L.shape[0]-1, y+1),x] - L[max(0, y-1),x]
    dx = L[y,min(L.shape[1]-1, x+1)] - L[y,max(0, x-1)]
    return cart_to_polar_grad(dx, dy)
# Simply converts the continuous angle of the gradient to a histogram bin
def quantize_orientation(theta, num_bins):
    bin_width = 360//num_bins
    return int(np.floor(theta)//bin_width)

def fit_parabola(hist, binno, bin_width):
    centerval = binno*bin_width + bin_width/2.

    if binno == len(hist)-1: rightval = 360 + bin_width/2.
    else: rightval = (binno+1)*bin_width + bin_width/2.

    if binno == 0: leftval = -bin_width/2.
    else: leftval = (binno-1)*bin_width + bin_width/2.

    A = np.array([
        [centerval**2, centerval, 1],
        [rightval**2, rightval, 1],
        [leftval**2, leftval, 1]])
    b = np.array([
        hist[binno],
        hist[(binno+1)%len(hist)],
        hist[(binno-1)%len(hist)]])

    x = LA.lstsq(A, b, rcond=None)[0]
    if x[0] == 0: x[0] = 1e-6
    return -x[1]/(2*x[0])
# To obtain the actual descriptors
def assign_orientation(kps, octave, num_bins=36):
    new_kps = []
    bin_width = 360//num_bins

    for kp in kps:
        cx, cy, s = int(kp[0]), int(kp[1]), int(kp[2])
        s = np.clip(s, 0, octave.shape[2]-1)

        sigma = kp[2]*1.5
        w = int(2*np.ceil(sigma)+1)
        kernel = gaussian_filter(sigma)

        L = octave[...,s]
        hist = np.zeros(num_bins, dtype=np.float32)

        for oy in range(-w, w+1):
            for ox in range(-w, w+1):
                x, y = cx+ox, cy+oy

                if x < 0 or x > octave.shape[1]-1: continue
                elif y < 0 or y > octave.shape[0]-1: continue

                m, theta = get_grad(L, x, y)
                weight = kernel[oy+w, ox+w] * m

                bin = quantize_orientation(theta, num_bins)
                hist[bin] += weight

        max_bin = np.argmax(hist)
        new_kps.append([kp[0], kp[1], kp[2], fit_parabola(hist, max_bin, bin_width)])

        max_val = np.max(hist)
        for binno, val in enumerate(hist):
            if binno == max_bin: continue

            if .8 * max_val <= val:
                new_kps.append([kp[0], kp[1], kp[2], fit_parabola(hist, binno, bin_width)])

    return np.array(new_kps)
```

In [74]:

```
# To calculate the gradients across the patch
def get_patch_grads(p):
    r1 = np.zeros_like(p)
    r1[-1] = p[-1]
    r1[:-1] = p[1:]

    r2 = np.zeros_like(p)
    r2[0] = p[0]
    r2[1:] = p[:-1]

    dy = r1-r2

    r1[:,-1] = p[:,-1]
    r1[:,:-1] = p[:,1:]

    r2[:,0] = p[:,0]
    r2[:,1:] = p[:,:-1]

    dx = r1-r2

    return dx, dy
# To create the histogram for each subregion
def get_histogram_for_subregion(m, theta, num_bin, reference_angle, bin_width, subregion_w):
    hist = np.zeros(num_bin, dtype=np.float32)
    c = subregion_w/2 - .5

    for i, (mag, angle) in enumerate(zip(m, theta)):
        angle = (angle-reference_angle) % 360
        binno = quantize_orientation(angle, num_bin)
        vote = mag

        # binno*bin_width is the start angle of the histogram bin
        # binno*bin_width+bin_width/2 is the center of the histogram bin
        # angle - " is the distance from the angle to the center of the bin
        hist_interp_weight = 1 - abs(angle - (binno*bin_width + bin_width/2))/(bin_width/2)
        vote *= max(hist_interp_weight, 1e-6)

        gy, gx = np.unravel_index(i, (subregion_w, subregion_w))
        x_interp_weight = max(1 - abs(gx - c)/c, 1e-6)
        y_interp_weight = max(1 - abs(gy - c)/c, 1e-6)
        vote *= x_interp_weight * y_interp_weight

        hist[binno] += vote

    return hist
# Local Descriptor Creation
def get_local_descriptors(kps, octave, w=16, num_subregion=4, num_bin=8):
    descs = []
    bin_width = 360//num_bin

    for kp in kps:
        cx, cy, s = int(kp[0]), int(kp[1]), int(kp[2])
        s = np.clip(s, 0, octave.shape[2]-1)
        kernel = gaussian_filter(w/6) # gaussian_filter multiplies sigma by 3
        L = octave[...,s]

        t, l = max(0, cy-w//2), max(0, cx-w//2)
        b, r = min(L.shape[0], cy+w//2+1), min(L.shape[1], cx+w//2+1)
        patch = L[t:b, l:r]

        dx, dy = get_patch_grads(patch)

        if dx.shape[0] < w+1:
            if t == 0: kernel = kernel[kernel.shape[0]-dx.shape[0]:]
            else: kernel = kernel[:dx.shape[0]]
        if dx.shape[1] < w+1:
            if l == 0: kernel = kernel[kernel.shape[1]-dx.shape[1]:]
            else: kernel = kernel[:dx.shape[1]]

        if dy.shape[0] < w+1:
            if t == 0: kernel = kernel[kernel.shape[0]-dy.shape[0]:]
            else: kernel = kernel[:dy.shape[0]]
        if dy.shape[1] < w+1:
            if l == 0: kernel = kernel[kernel.shape[1]-dy.shape[1]:]
            else: kernel = kernel[:dy.shape[1]]
```

```
            else: kernel = kernel[:dy.shape[1]]

        m, theta = cart_to_polar_grad(dx, dy)
        dx, dy = dx*kernel, dy*kernel

        subregion_w = w//num_subregion
        featvec = np.zeros(num_bin * num_subregion**2, dtype=np.float32)

        for i in range(0, subregion_w):
            for j in range(0, subregion_w):
                t, l = i*subregion_w, j*subregion_w
                b, r = min(L.shape[0], (i+1)*subregion_w), min(L.shape[1], (j+1)*subregion_w)

                hist = get_histogram_for_subregion(m[t:b, l:r].ravel(),
                                                theta[t:b, l:r].ravel(),
                                                num_bin,
                                                kp[3],
                                                bin_width,
                                                subregion_w)
                featvec[i*subregion_w*num_bin + j*num_bin:i*subregion_w*num_bin + (j+1)*num_bin] = h
ist.flatten()

        featvec /= max(1e-6, LA.norm(featvec))
        featvec[featvec>0.2] = 0.2
        featvec /= max(1e-6, LA.norm(featvec))
        descs.append(featvec)

    return np.array(descs)
```

In [89]:

```
class SIFT(object):
    def __init__(self, im, s=3, num_octave=4, s0=1.3, sigma=1.6, r_th=10, t_c=0.03, w=16):
        self.im = ndimage.convolve(rgb2gray(im), gaussian_filter(s0))
        self.s = s
        self.sigma = sigma
        self.num_octave = num_octave
        self.t_c = t_c
        self.R_th = (r_th+1)**2 / r_th
        self.w = w

    def get_features(self):
        gaussian_pyr = generate_gaussian_pyramid(self.im, self.num_octave, self.s, self.sigma)
        DoG_pyr = generate_DoG_pyramid(gaussian_pyr)
        kp_pyr = get_keypoints(DoG_pyr, self.R_th, self.t_c, self.w)
        feats = []

        for i, DoG_octave in enumerate(DoG_pyr):
            kp_pyr[i] = assign_orientation(kp_pyr[i], DoG_octave)
            feats.append(get_local_descriptors(kp_pyr[i], DoG_octave))

        self.kp_pyr = kp_pyr
        self.feats = feats

        return feats
```

In [ ]:

```
if __name__ == '__main__':
    num_img = 3

    kp_pyrs = []
    ims = []

    for i in range(1, num_img+1):
        im = imread('NotreDame1.JPG')
        im = imread('NotreDame2.JPG')

        sift_detector = SIFT(im)
        _ = sift_detector.get_features()
        kp_pyrs.append(sift_detector.kp_pyr)

    for i in range(len(kp_pyrs[0])):
        _, ax = plt.subplots(1, 3)
        ax[0].imshow(ims[0])
```

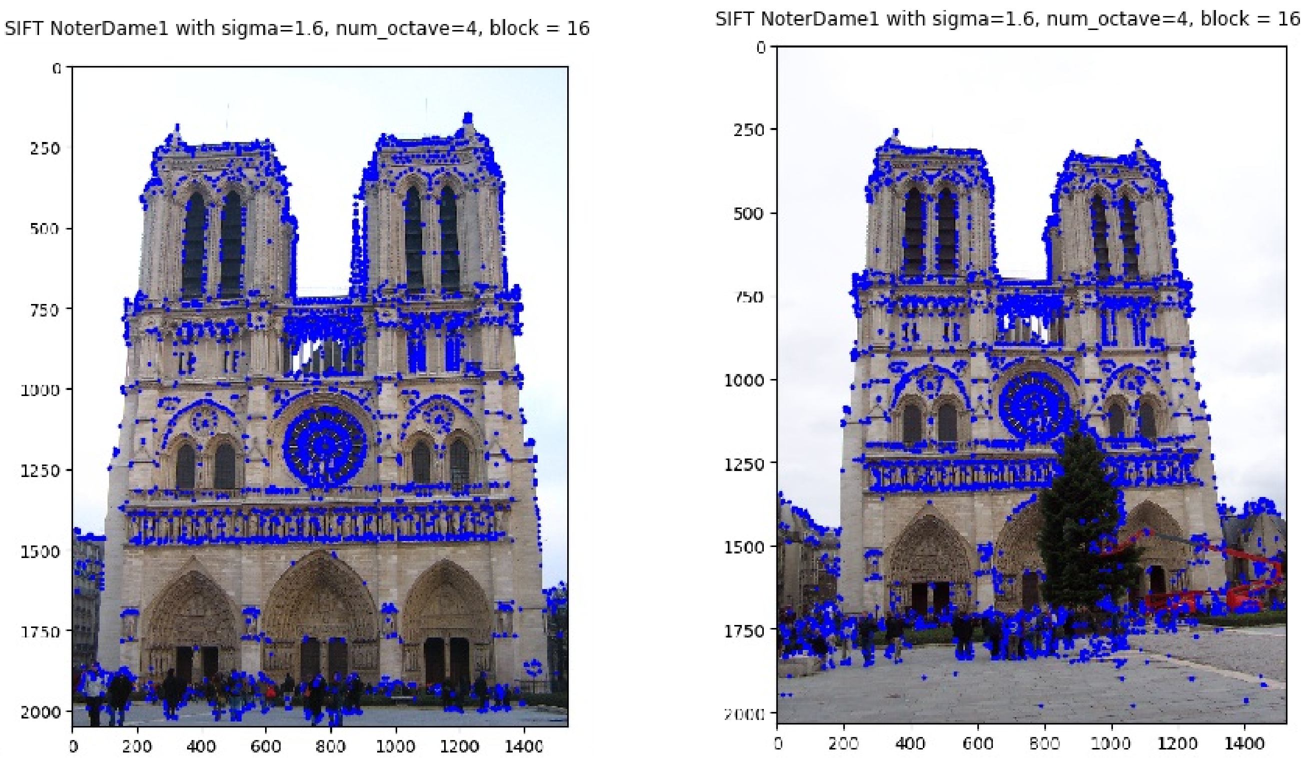
```
        kps = kp_pyrs[0][i]*(2**i)
        ax[0].scatter(kps[:,0], kps[:,1], c='b', s=2.5)

        ax[1].imshow(ims[1])

        kps = kp_pyrs[1][i]*(2**i)
        ax[1].scatter(kps[:,0], kps[:,1], c='b', s=2.5)

        ax[2].imshow(ims[2])

        kps = kp_pyrs[2][i]*(2**i)
        ax[2].scatter(kps[:,0], kps[:,1], c='b', s=2.5)

        plt.show()
```

In [98]:

```
# Vis
sift_img1 = cv2.imread('sift_img1.PNG')
sift_img2 = cv2.imread('sift_img2.PNG')
fig, (ax1, ax2)=plt.subplots(1, 2, figsize = (15,15), sharey=True)

ax1.imshow(cv2.cvtColor(sift_img1, cv2.COLOR_BGR2RGB))
ax1.set_title('SIFT NoterDame1 with sigma=1.6, num_octave=4, block = 16')
ax1.axis('off')

ax2.imshow(cv2.cvtColor(sift_img2, cv2.COLOR_BGR2RGB))
ax2.set_title('SIFT NoterDame1 with sigma=1.6, num_octave=4, block = 16')
ax2.axis('off')
```

Out[98]:

```
(-0.5, 489.5, 605.5, -0.5)
```



3. Find matches among the key points using different (Euclidian, cosine similarity, correlation, SSD,Nearest neighbor ratio)

Euclidian Matching

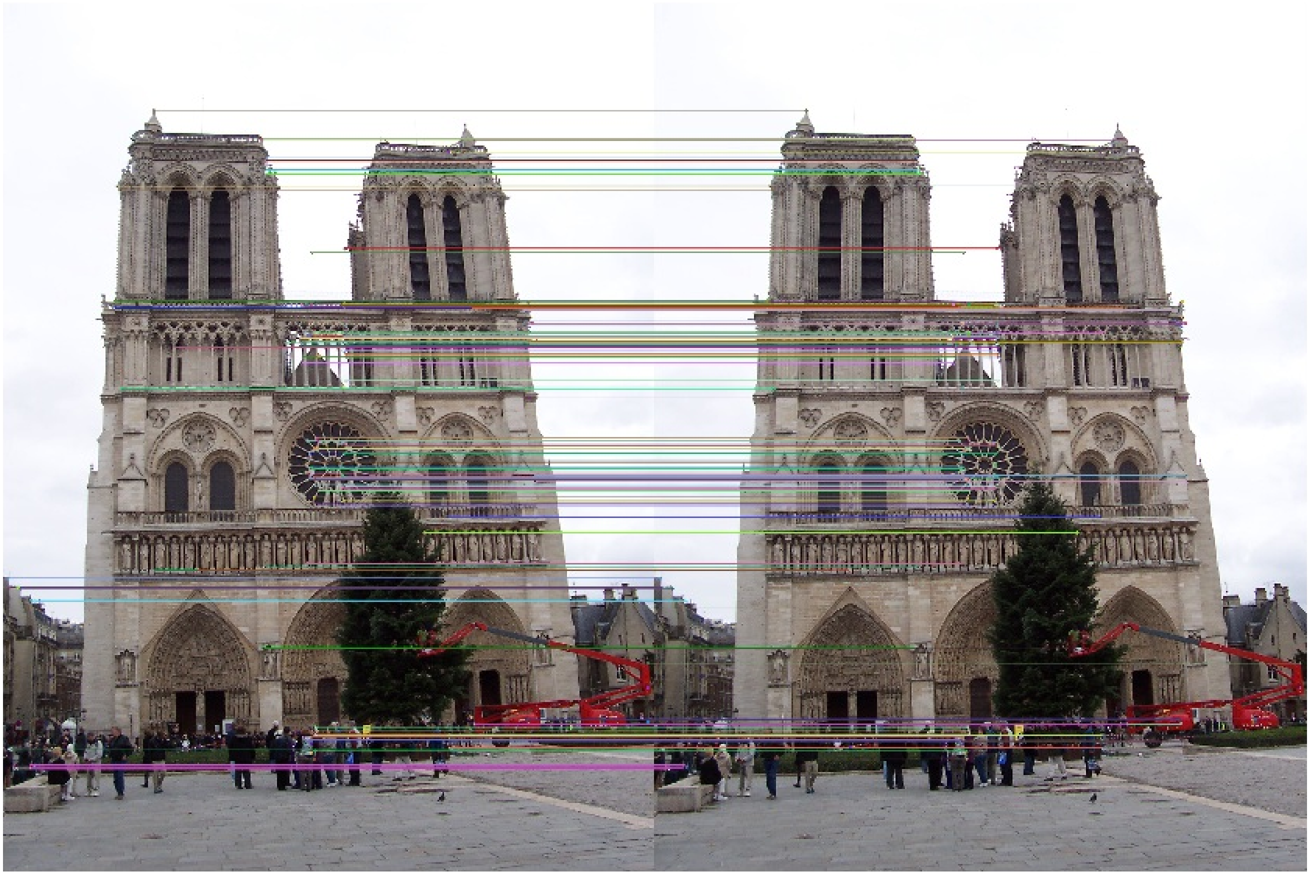
In [23]:

```
# Read Images
img1 = cv2.imread('NotreDame1.jpg')
img1 = cv2.imread('NotreDame2.jpg')
```

```python
# instantiate SIFT object
sift = cv2.xfeatures2d.SIFT_create(2000)
# calculate keypoints and their orientation
kps_1, descriptors_1 = sift.detectAndCompute(img1, None)
kps_2, descriptors_2 = sift.detectAndCompute(img2, None)
print("SIFT detected Keypoints", len(kps_1))
print("SIFT detected Keypoints", len(kps_2))
# create BFMatcher object
bf = cv2.BFMatcher()
# Match descriptors.
matches = bf.match(descriptors_1,descriptors_2)
# Sort them in the order of their distance.
matches = sorted(matches, key = lambda x:x.distance)

# Draw first 300 matches
img3 = cv2.drawMatches(cv2.cvtColor(img1, cv2.COLOR_BGR2RGB),kps_1,cv2.cvtColor(img2, cv2.COLOR_BGR
2RGB),kps_2,matches[:300], None, flags=2)
plt.figure(figsize = (15,15)), plt.imshow(img3),plt.axis('off'),plt.title('Features Matching by
Euclidian distance with SIFT detector'), plt.show()
```

```
SIFT detected Keypoints 2001
SIFT detected Keypoints 2001
```

Features Matching by Euclidian distance with SIFT detector



Out[23]:

```
(<Figure size 1080x1080 with 1 Axes>,
 <matplotlib.image.AxesImage at 0x13232d95748>,
 (-0.5, 3047.5, 2031.5, -0.5),
 Text(0.5, 1, 'Features Matching by Euclidian distance with SIFT detector'),
 None)
```

Feature Matching by Nearest Neighbor Distance Ratio

In [26]:

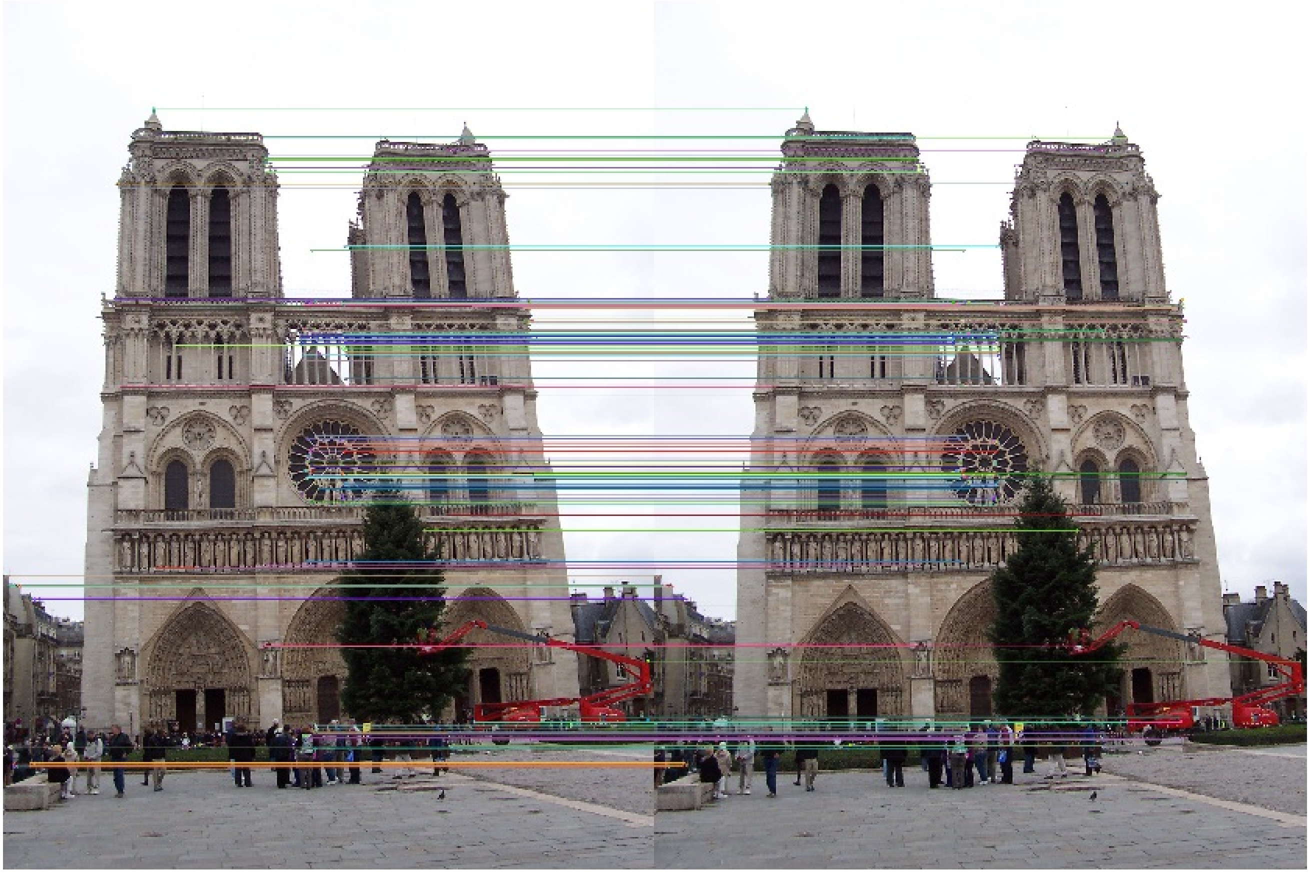
```python
# matching the descriptors from both the images
bf = cv2.BFMatcher()
matches = bf.knnMatch(descriptors_1,descriptors_2,k = 2)
# selecting only the good features with KNN
```

```
good_matches = []
ratio = 0.75
for m,n in matches:
    if m.distance < ratio*n.distance:
        good_matches.append([m])

image3 = cv2.drawMatchesKnn(cv2.cvtColor(img1, cv2.COLOR_BGR2RGB),kps_1,cv2.cvtColor(img2, cv2.COLO
R_BGR2RGB),kps_2,good_matches[:300], None, flags = 2)
plt.figure(figsize = (15,15))
plt.title('Features Matching by Nearest Neighbor Distance Ratio with K = 2')
plt.axis('off')
plt.imshow(image3)
```

Out[26]:

```
<matplotlib.image.AxesImage at 0x13233425e48>
```

Features Matching by Nearest Neighbor Distance Ratio with K = 2



Note: If you decrease the ratio value, for example to 0.1 you will get really high quality matches, but the downside is that you will get only few matches.

4. Manually/Automatically chose at least four matching pair and represent and show them as Ah=0 form, where h is projective transformation / homography parameters.

In [28]:

```
# Computers a homography from 4-correspondences
randomFour = []
def calculateHomography(correspondences):
    #loop through correspondences and create assemble matrix
    aList = []
    for corr in correspondences:
        p1 = np.matrix([corr.item(0), corr.item(1), 1])
        p2 = np.matrix([corr.item(2), corr.item(3), 1])

        a2 = [0, 0, 0, -p2.item(2) * p1.item(0), -p2.item(2) * p1.item(1), -p2.item(2) * p1.item(2),
              p2.item(1) * p1.item(0), p2.item(1) * p1.item(1), p2.item(1) * p1.item(2)]
        a1 = [-p2.item(2) * p1.item(0), -p2.item(2) * p1.item(1), -p2.item(2) * p1.item(2), 0, 0, 0,
              p2.item(0) * p1.item(0), p2.item(0) * p1.item(1), p2.item(0) * p1.item(2)]
        aList.append(a1)
```

```
        aList.append(a1)
        aList.append(a2)

    matrixA = np.matrix(aList)

    #svd composition
    u, s, v = np.linalg.svd(matrixA)

    #reshape the min singular value into a 3 by 3 matrix
    h = np.reshape(v[8], (3, 3))

    #normalize and now we have h
    h = (1/h.item(8)) * h
    return h

# Calculate the geometric distance between estimated points and original points
def geometricDistance(correspondence, h):

    p1 = np.transpose(np.matrix([correspondence[0].item(0), correspondence[0].item(1), 1]))
    estimatep2 = np.dot(h, p1)
    estimatep2 = (1/estimatep2.item(2))*estimatep2

    p2 = np.transpose(np.matrix([correspondence[0].item(2), correspondence[0].item(3), 1]))
    error = p2 - estimatep2
    return np.linalg.norm(error)

# Runs through ransac algorithm, creating homographies from random correspondences
def ransac(corr, thresh):
    maxInliers = []
    finalH = None
    for i in range(1000):
        #find 4 random points to calculate a homography
        corr1 = corr[random.randrange(0, len(corr))]
        corr2 = corr[random.randrange(0, len(corr))]
        randomFour = np.vstack((corr1, corr2))
        corr3 = corr[random.randrange(0, len(corr))]
        randomFour = np.vstack((randomFour, corr3))
        corr4 = corr[random.randrange(0, len(corr))]
        randomFour = np.vstack((randomFour, corr4))

        #call the homography function on those points
        h = calculateHomography(randomFour)
        inliers = []

        for i in range(len(corr)):
            d = geometricDistance(corr[i], h)
            if d < 5:
                inliers.append(corr[i])

        if len(inliers) > len(maxInliers):
            maxInliers = inliers
            finalH = h
       # print ("Corr size: ", len(corr), " NumInliers: ", len(inliers), "Max inliers: ",
len(maxInliers))

        if len(maxInliers) > (len(corr)*thresh):
            break
    return finalH, maxInliers, randomFour
```

In [30]:

```
# Main parses argument list and runs the functions
estimation_thresh = 0.60

#query image
img1 = cv2.imread('NotreDame1.jpg')
#train image
img2 = cv2.imread('NotreDame2.jpg')
sift = cv2.xfeatures2d.SIFT_create()
# calculate keypoints and their orientation
kps_1, descriptors_1 = sift.detectAndCompute(img1, None)
kps_2, descriptors_2 = sift.detectAndCompute(img2, None)
# create BFMatcher object
bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True)
# Match descriptors.
matches = bf.match(descriptors_1,descriptors_2)
# Sort them in the order of their distance
```

```
# Sort them in the order of their distance.
matches = sorted(matches, key = lambda x:x.distance)

# Find features and keypoints
correspondenceList = []
keypoints = [kps_1,kps_2]
for match in matches:
    (x1, y1) = keypoints[0][match.queryIdx].pt
    (x2, y2) = keypoints[1][match.trainIdx].pt
    correspondenceList.append([x1, y1, x2, y2])

corrs = np.matrix(correspondenceList)

# Run ransac algorithm
finalH, inliers, randomFour = ransac(corrs, estimation_thresh)
Homography_Mat = finalH
```

```
Final inliers count:  1427
```

In [38]:

```
print('\nRandom Four points by RANSAC Algorithm:\n\n', np.int0(randomFour))
```

```
Random Four points by RANSAC Algorithm:

 [[1306  596  529 1340]
 [1290 1447 1211 1296]
 [1003  962  961  906]
 [ 308 1090  717  940]]
```

5. Find homography matrix H by solving the Eqn Ah=0 using the technique of solving Homogeneous linear system or Homogeneous least square linear system.

In [44]:

```
# Homography Matrix
print ("\nHomography Matrix: \n\n", Homography_Mat)
# Count inliers through RANSAC Algorithm
print ("\nFinal inliers count: ", len(inliers))
```

```
Homography Matrix:

 [[ 9.18243571e-01  2.87152940e-02  5.94962796e+01]
 [ 9.98653032e-02  8.09372391e-01  7.50341831e+01]
 [ 8.26893237e-05 -3.15529440e-05  1.00000000e+00]]

Final inliers count:  1427
```

6. Apply H to transform first image into a homographic transformed version using backward warping, also show all the images (first, 2nd, and the homographic transformed) side-by-side. Also show the difference between 2nd and transformed images.

In [72]:

```
# Homography Matrix
Homography_Mat = Homography_Mat
# Homographic Tranformed done by Homographic Matrix of Image 1
homographic_transformed = cv2.warpPerspective(img1,Homography_Mat, (img2.shape[1], img2.shape[0]),
flags=cv2.INTER_LINEAR) # image, H-Matrix, img shape, flags = Bilinear Interpolation
# Difference Between 2nd and Homographic Transform image
difference = img2 - homographic_transformed

# Visualization
fig, ax=plt.subplots(2, 2, figsize = (15,15))

ax[0,0].imshow(cv2.cvtColor(img1, cv2.COLOR_BGR2RGB))
ax[0,0].set_title('NoterDame1')
ax[0,0].axis('off')

ax[0,1].imshow(cv2.cvtColor(img2, cv2.COLOR_BGR2RGB))
ax[0,1].set_title('NoterDame2')
```

```python
ax[0,1].set_title('NoterDame2')
ax[0,1].axis('off')

ax[1,0].imshow(cv2.cvtColor(homographic_transformed, cv2.COLOR_BGR2RGB))
ax[1,0].set_title('Homographic Transform NoterDame1 with Bilinear Interpolation')
ax[1,0].axis('off')

ax[1,1].imshow(difference, cmap = 'gray')
ax[1,1].set_title('Dfifference between NoterDame2 and Transformed image')
ax[1,1].axis('off')

plt.tight_layout()
plt.show()
```

In [ ]:

```python

```

Go to Top