

# Implementation of Normalised Cross-correlation Based Template Matching Method

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GNR 602 - Programing Assignment |

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# TEMPLATE MATCHING

- **Template matching**

Template Matching is a methodology in digital image processing to identify little components of a figure which match a template image. It is used to match a template to an image wherever the template is a sub image which contains the form which we want to find out. Templates are usually employed to print characters, identify numbers, and other little, simple objects. It can be used for detection of edges in figures.

- **Source image**

An image in which we are hoping to find template image.

- **Template Image**

The patch image that can be compared to the template image and our objective is to discover the most effective technique for the best matching region.



# Template Matching Approaches

- **Featured-based approach**

The Featured-based method is appropriate while both reference and template images have more connection with regards to features and control points. The features comprises of points, a surface model which needs to be matched, and curves

- **Area-based approach**

Area-based methods merge the matching part with the feature detection step. These techniques manage the pictures without attempting to identify the remarkable article. Windows of predefined size are used for the estimation of correspondence.

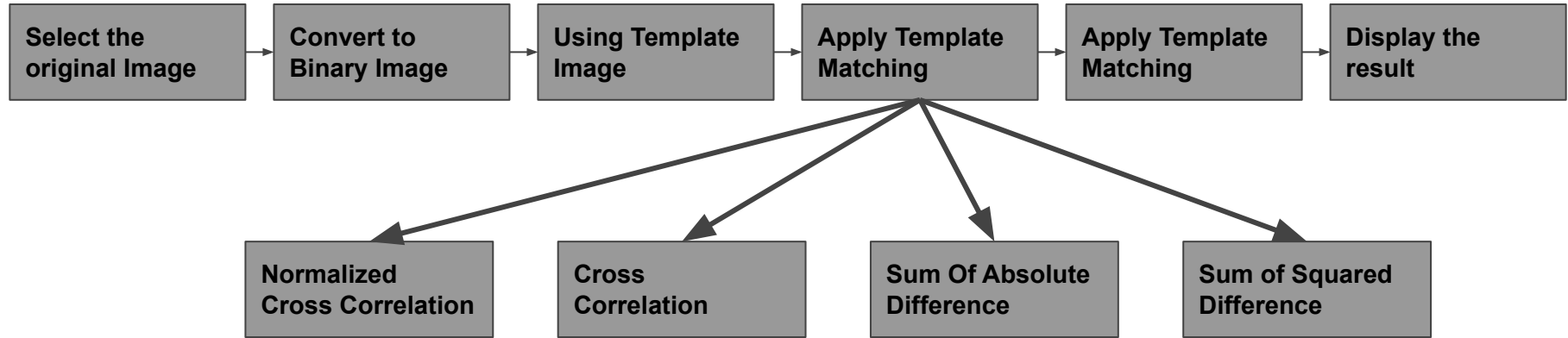
- **Template-based approach**

Template-based template matching approach could probably require sampling of a huge quantity of points, it's possible to cut back the amount of sampling points via diminishing the resolution of the search and template images via the same factor and performs operation on resulting downsized images

- **Motion Tracking and Occlusion Handling**

For the templates which can't provide and may not provide an instantaneous match, in that case Eigen spaces may be used, which provides the details of matching image beneath numerous conditions.

# Methodology



# Techniques

## 1. Naive template matching

In this technique the template is positioned over the image at every possible location, and each time some numeric measure of similarity between the template and the image segment it currently overlaps with is calculated. Finally the position with best similarity measure is identified.

## 2. Image Correlation Matching

This method overcomes the Naive template matching problems like computing similarity patterns in aligned pattern images.

### a) Cross-Correlation

This method is basically a simple sum of pairwise multiplications of corresponding pixel values of the image.

### b) Normalized cross-correlation

This method is an improvisation on cross correlation. This improvisations are

- The outcomes are constant to the global brightness changes, that is darkening of whichever figure or consistent brightening have no impact on end results.
- The final correlation value is scaled to  $[-1, 1]$  range, in order that NCC of 2 alike figures is equal to 1.0

# Techniques

## 3. Sum of squared differences

In addition to template matching this technique is also used in noise and rotation detection test. In this method measure of variation or deviation from the mean is represented by sum of squares. It is calculated as a summations of the squares of the variations from the mean. The performance of this method is done by making the comparison based on the value of correlation coefficient and that produced from different template image

## Drawbacks of above techniques

These methods are inefficient as it is time-consuming in computing the pattern correlation image for images varying from medium to large images.



# Normalized cross-correlation

**Normalized cross-correlation** is an improved model of the traditional cross correlation methodology. Two major improvement of those are -

- Effect of darkening have no impact on end results. Thus the outcomes are constant wrt brightness changes
- The final correlation value is scaled to  $[-1, 1]$  range, in order that NCC of 2 alike figures is equal to 1.0
- Formula of NCC is

$$\frac{1}{N\sigma_1\sigma_2\sigma_3} \sum_{u,v} [(image1(u,v) - \overline{image1}) \times (image2(u,v) - \overline{image2})]$$

Where image1 and image2 are two images. u and v are their respective pixel coordinates.  $\Sigma$  is a constant



# Normalized cross-correlation

- **Benefits**

Conventional correlation-based image matching techniques not succeed in case if there are significant scale changes or large rotations among the two figures. But Normalized cross-correlation can be give efficient resemblance measure meant for matching applications

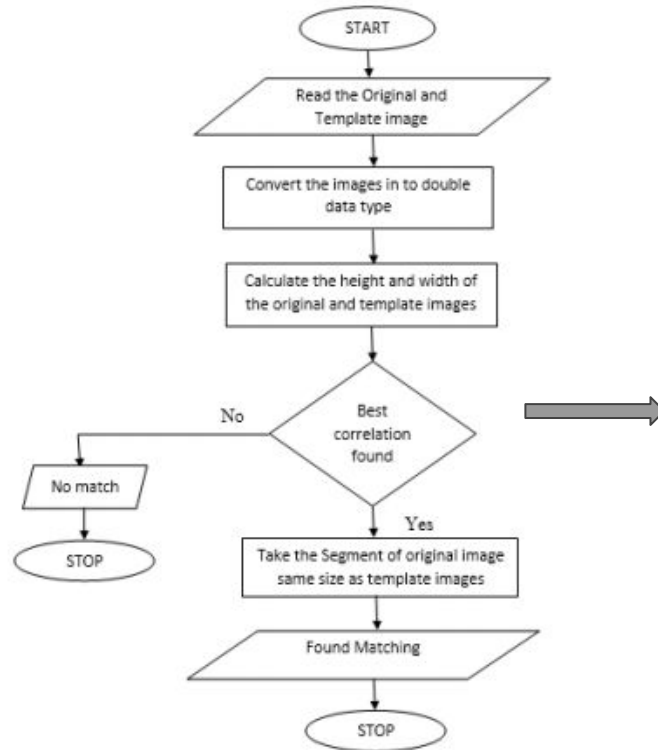
- **Drawbacks**

Normalized Cross Correlation is more complicated as compared to both SSD and SAD algorithms as it entails several division, square root operations and multiplication. In case of NCC, there's a big increase within the inaccuracy rate which is because of the shaded input figure





# Workflow



**Has two types  
in our case**

## Packages Required

- Numpy
- Opencv-python
- Matplotlib



## Code Snippets

- This is our function to calculate calculate Normalized Cross correlation value , it takes target image and the cropped source image(with the same number of pixel as of target image) as input

```
def Normalized_Cross_Correlation(roi,  
target):  
    cor = np.sum(roi * target)  
    nor = np.sqrt( (np.sum(roi ** 2))) *  
np.sqrt(np.sum(target ** 2))  
    #print(cor/nor)  
    return cor / nor
```

# Code Snippets

## Type I

### Template Match Function

def tm(img, target):

```
img_height, img_width = img.shape
tar_height, tar_width = target.shape
(max_Y, max_X) = (0, 0)
MaxValue = 0
```



Storing the Image and target dimensions along with coordinates of point on image plane which have maximum NCC till now along with its value

```
NccVal = np.zeros((img_height-tar_height, img_width-tar_width))
```

```
img = np.array(img, dtype="int")
target = np.array(target, dtype="int")
```



Converting Image and target into Numpy array time ,Also initializing a zero valued Numpy array for NCC value



# Code Snippets

## Type I

```
for y in range(0, img_height-tar_height):
```

```
    for x in range(0, img_width-tar_width):
```

```
        roi = img[y : y+tar_height, x : x+tar_width]
```

```
        NccVal[y, x] = Normalized_Cross_Correlation(roi, target)
```

```
    if NccVal[y, x] > 0.975:
```

```
        MaxValue = NccVal[y, x]
```

```
        (max_Y, max_X) = (y, x)
```

```
        print(MaxValue)
```

```
        top_left = (max_X, max_Y)
```

```
        cv2.rectangle(image, top_left, (top_left[0] + target.shape[1], top_left[1] + target.shape[0]), 0, 3)
```

```
    return (max_X, max_Y)
```

Calculating NCC for every valid pixel coordinate in image. Here in Type 1 we have made a rectangle for every pixel coordinate which gave NCC value greater than 0.975

Might be used to recognize more than one instance



# Code Snippets

## Type II

```
def tm(img, target):
```

```
    img_height, img_width = img.shape  
    tar_height, tar_width = target.shape  
    (max_Y, max_X) = (0, 0)  
    MaxValue = 0
```



Storing the Image and target dimensions along with coordinates of point on image plane which have maximum NCC till now along with its value

```
NccVal = np.zeros((img_height-tar_height, img_width-tar_width))
```

```
img = np.array(img, dtype="int")  
target = np.array(target, dtype="int")
```



Converting Image and target into Numpy array time ,Also initializing a zero valued Numpy array for NCC value



# Code Snippets

## Type II

```
for y in range(0, img_height-tar_height):
```

```
    for x in range(0, img_width-tar_width):
```

```
        roi = img[y : y+tar_height, x : x+tar_width]
```

```
        NccVal[y, x] = Normalized_Cross_Correlation(roi, target)
```

```
        if NccVal[y, x] > MaxValue:
```

```
            MaxValue = NccVal[y, x]
```

```
            (max_Y, max_X) = (y, x)
```

```
            print(MaxValue)
```

```
top_left = (max_X, max_Y)
```

```
cv2.rectangle(image, top_left, (top_left[0] + target.shape[1], top_left[1] + target.shape[0]), 0, 3)
```

```
return (max_X, max_Y)
```



Calculating NCC for every valid pixel coordinate in image

Here in type 2 we are only drawing a rectangle corresponding to pixel with highest NCC value  
Thus only one instance recognized



# Code Snippets

## Main Function

```
if __name__ == '__main__':
```

```
    ap = argparse.ArgumentParser()
    ap.add_argument("-i", "--image", required = True, help = "Path to input image")
    ap.add_argument("-t", "--target", required = True, help = "Path to target")
    args = vars(ap.parse_args())
```

```
    image = cv2.imread(args["image"], 0)
    target = cv2.imread(args["target"], 0)
```



Taking input of source and target image through command line

```
    #cv2.imshow("image", image)
    #cv2.waitKey(0)
```

```
    height, width = target.shape
    top_left = tm(image, target)
```

```
    #draws a rectangle based on the info received
    cv2.rectangle(image, top_left, (top_left[0] + width, top_left[1] + height), 0, 3)
```

```
    pl.subplot(111)
    pl.imshow(image)
    pl.title('result')
    pl.show()
```



Drawing the rectangle based on the response received



## How to run?

- From the Command Line Change Directory(through cd) to the project directory
- From there use the command

“python Type1.py -i B.jpg -t A.jpg” for Type 1

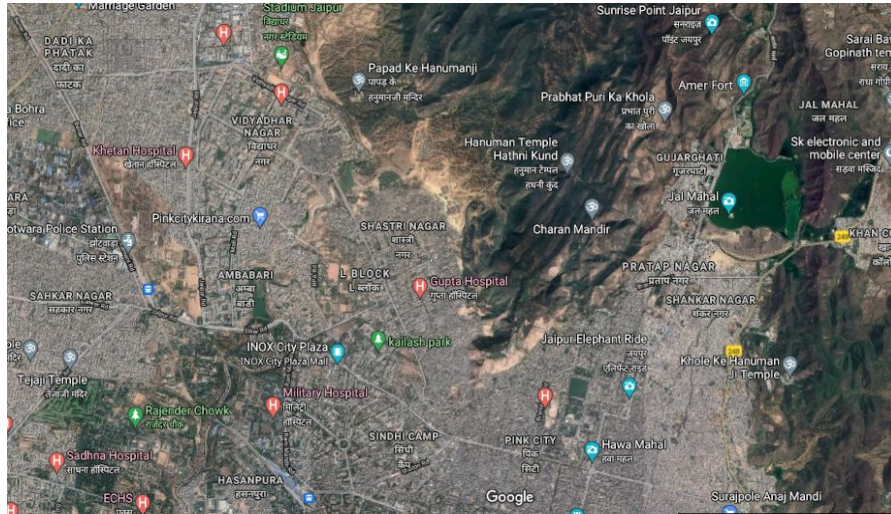
“python Type2.py -i B.jpg -t A.jpg” for Type 2

\*Replace A and B by Image names A-Source Image    B-Target Image



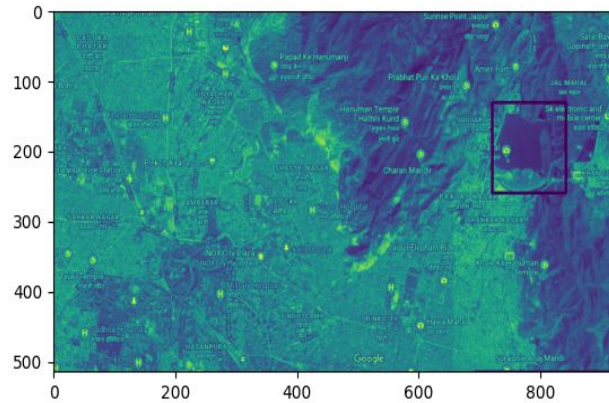
# Results

## 1.Input

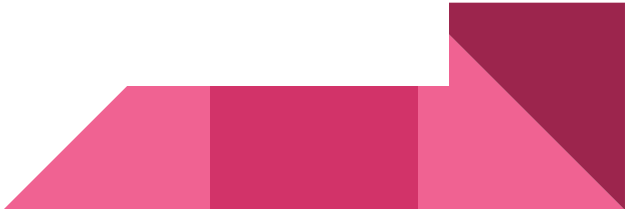
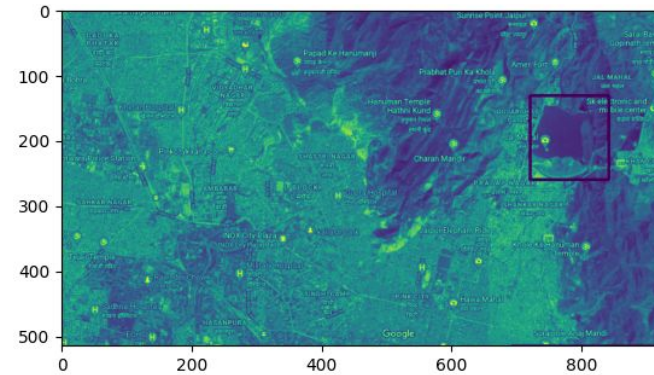


## Results

## Type I

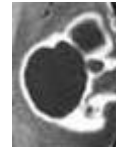
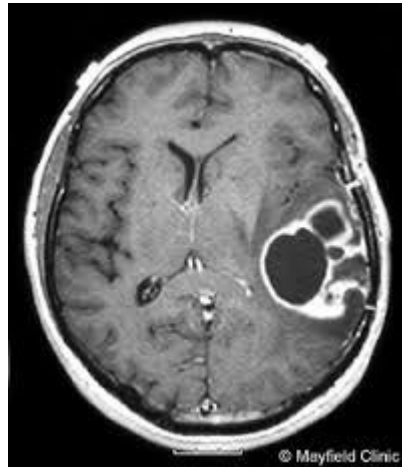


## Type I



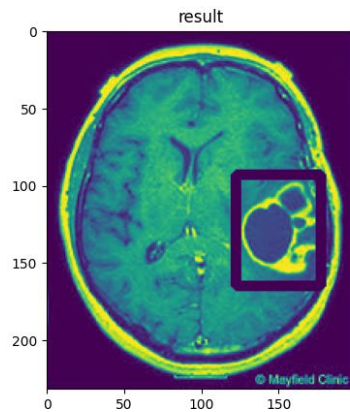
# Results

## 2. Input

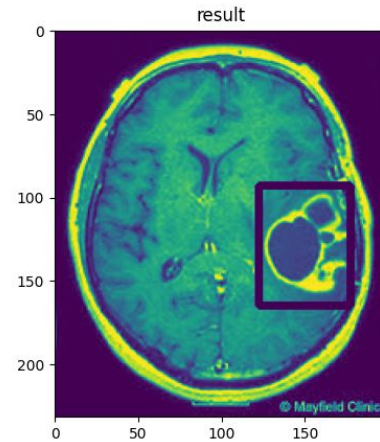


# Results

## Type I



## Type II



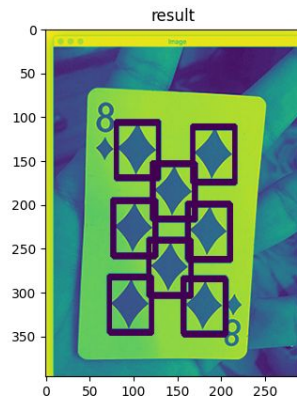
# Results

## 3. Input

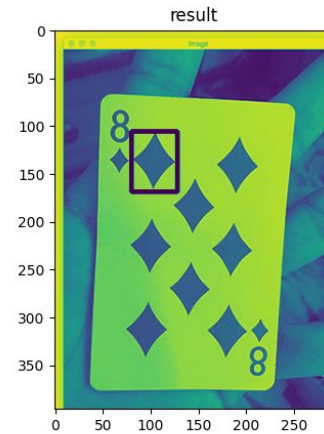


# Results

## Type I



## Type II



# Results

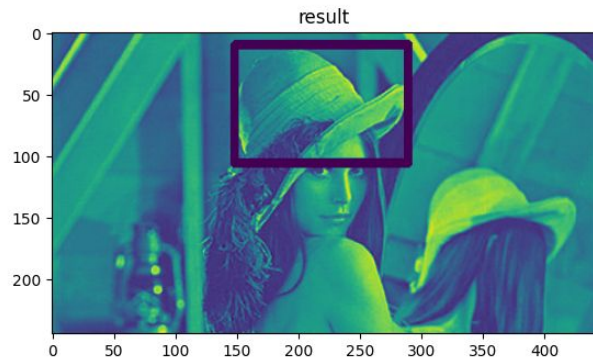
## 4. Input



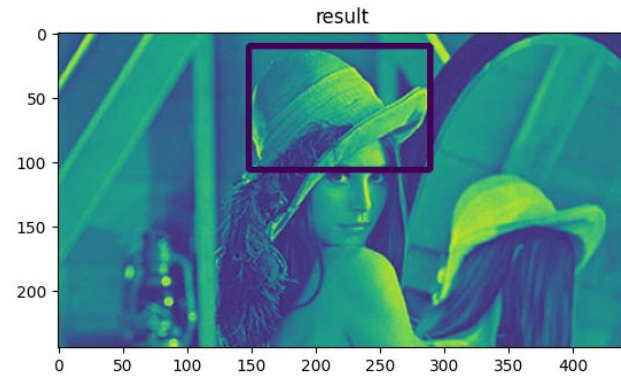


# Results

## Type I



## Type II

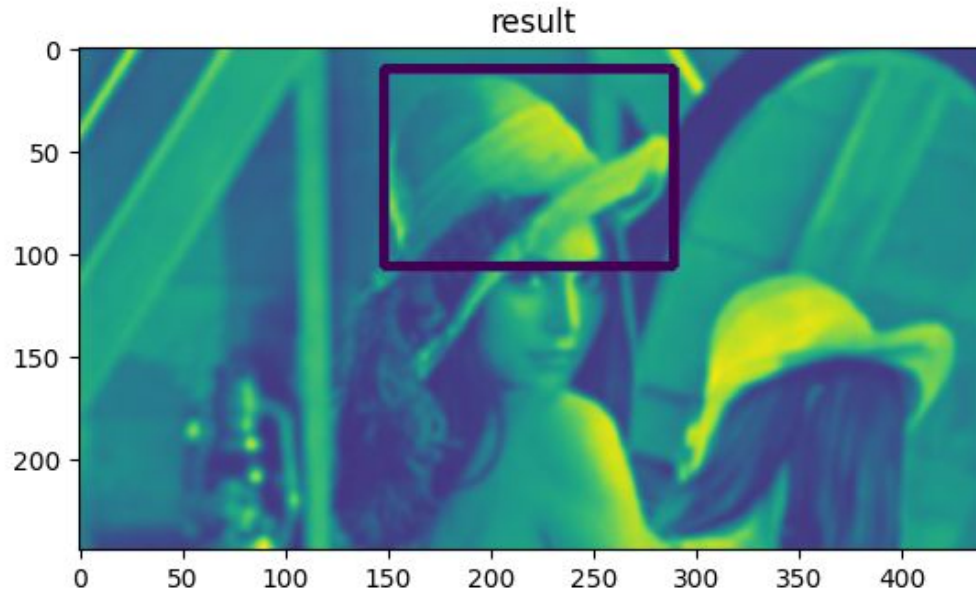


# Results

## 5. Input [Gaussian Blur with Kernel=13]



# Results



Observation: Max NCC Value  
was reduced

## Further Possibilities

- By taking advantage of the exhaustive search and high overlap between windows required for high-quality imaging, this method can avoid redundant calculation in motion estimation and thereby significantly reduce the computational cost.
- Finding correspondences always remains a very active area of research. The Registration and correspondences of images in turn is based on cross correlation and normalized cross correlation techniques have been studied the least and they are an active area of research.
- The algorithm can be further developed to achieve conversion to many number systems such as hexadecimal and octal.
- This method could thus prove very useful in real-time motion estimation in medical ultrasound as well as other medical imaging modalities or computational fields.
- The betterment or deterioration of the severity of a patient's disease, can also be monitored on a time to time basis by NCC.



## References

1. [https://docs.adaptive-vision.com/4.7/studio/machine\\_vision\\_guide/TemplateMatching.html](https://docs.adaptive-vision.com/4.7/studio/machine_vision_guide/TemplateMatching.html)
2. <https://www.ijcaonline.org/archives/volume153/number10/swaroop-2016-ijca-912165.pdf>
3. [https://www.ripublication.com/acst17/acstv10n1\\_07.pdf](https://www.ripublication.com/acst17/acstv10n1_07.pdf)
4. <https://www.youtube.com/watch?v=ngEC3sXeUb4>