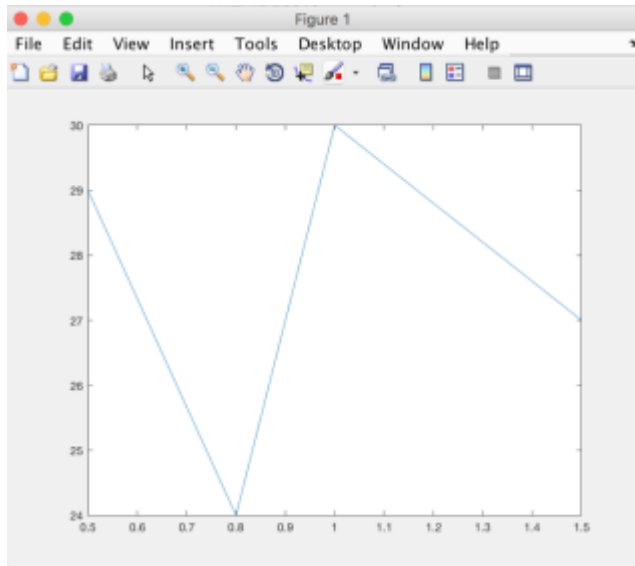


SIFT AND MOPS OF IMAGE DATABASE

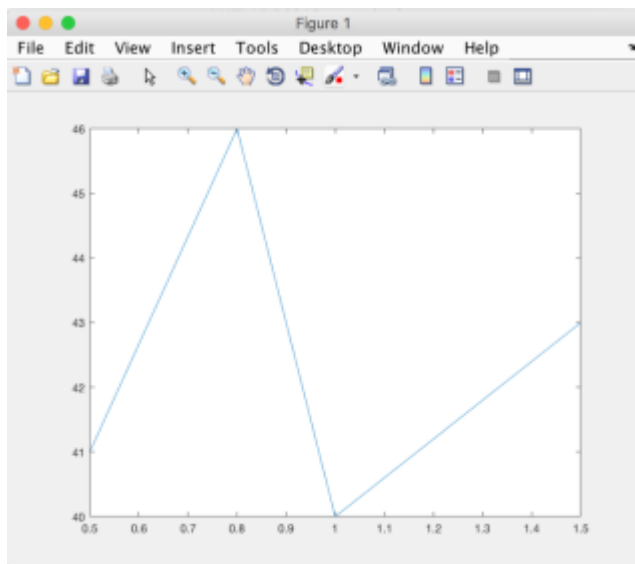
Shreyas Pattabiraman UIN: 674434423

MOPS:

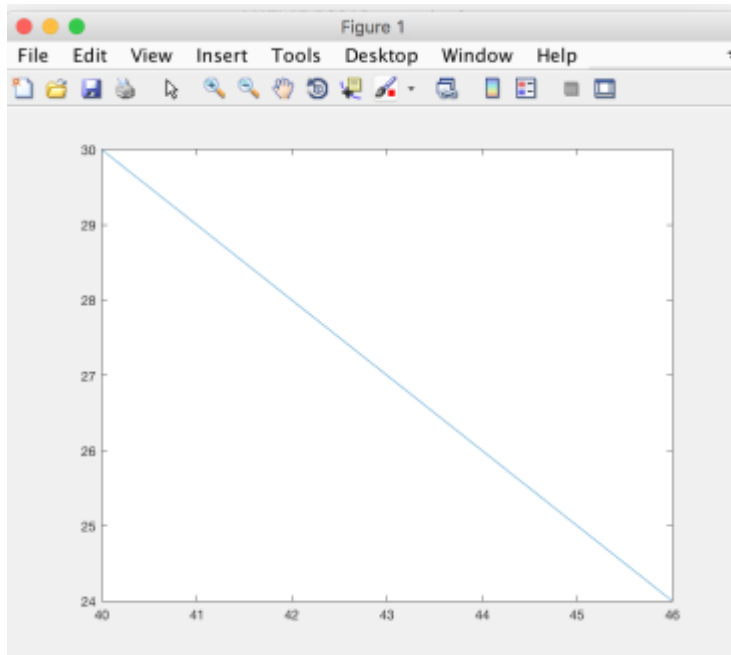
Plot for Threshold vs False Positive



Plot for Threshold vs True Positive



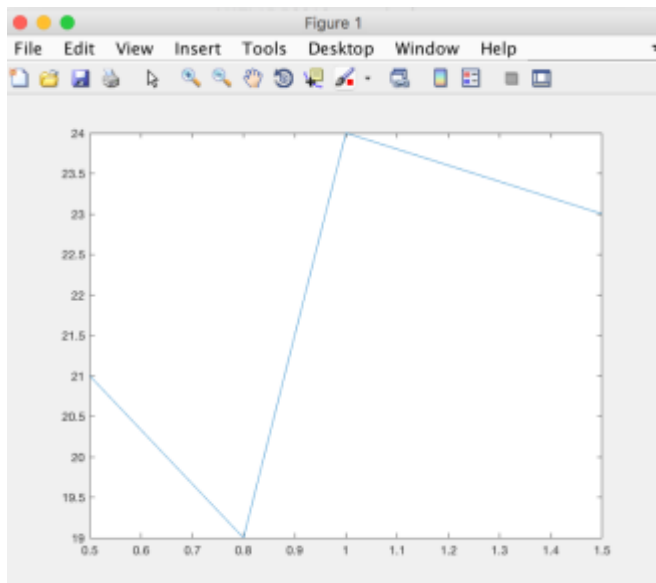
Plot for True Positive vs False Positive



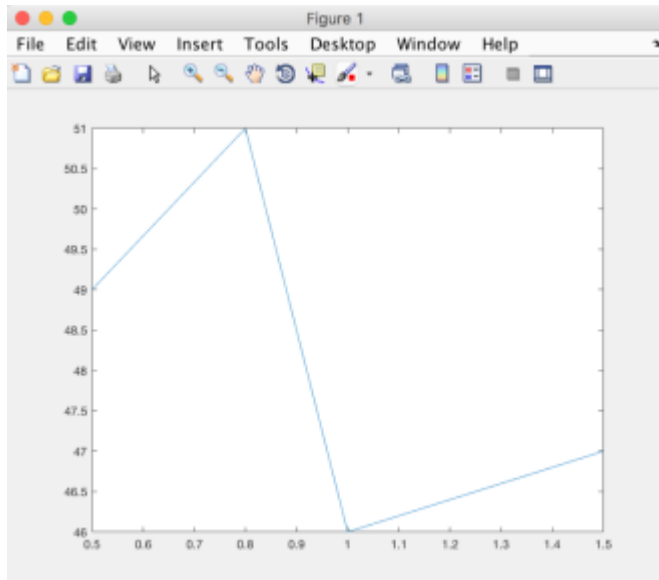
The above three plots are for MOPS descriptor feature extraction. The Thresholds used were 0.5, 0.8, 1, 1.5. The best threshold turned out to be 0.8. The true positives turned out to be maximum at threshold= 0.8 and they were less when the value varied. The plots for true positive and threshold was a pretty good evidence that 0.8 was the best threshold to use. The other plot was false positive vs true positive also showed pretty good evidence that the best threshold was 0.8.

SIFT:

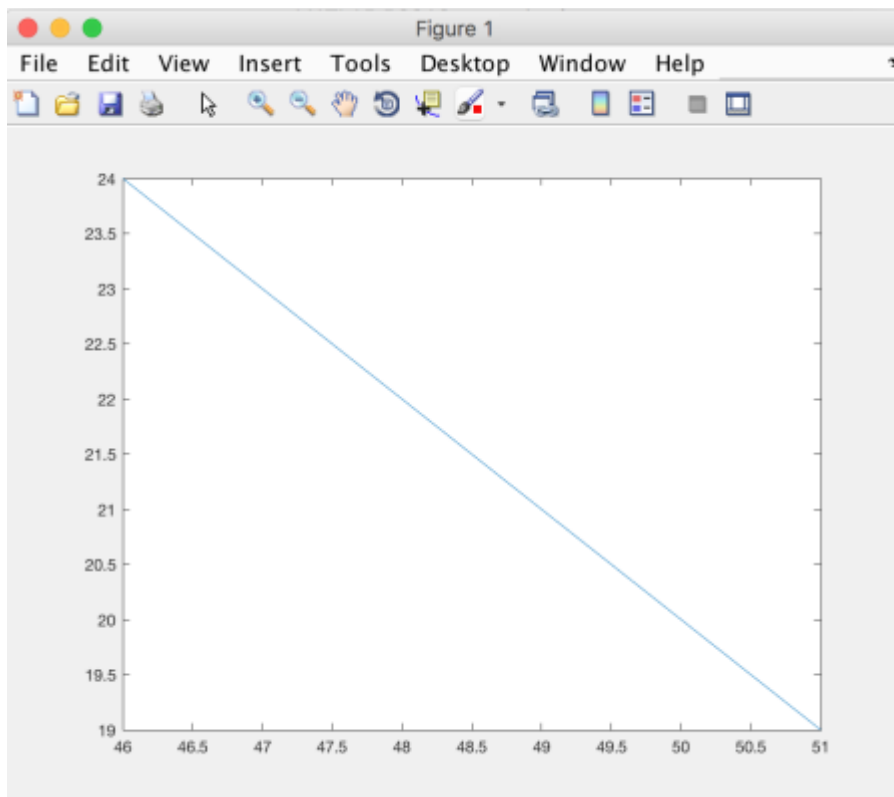
Plot for Threshold vs False Positive



Plot for Threshold vs True Positive



Plot for True Positive vs False Positive



The best threshold to use for SIFT was 0.8. The above three plots show that the different values for the threshold were chosen and the output. The plot for was between false positive and true positive. Threshold was implemented in SIFT feature description. The best threshold used was determined to be 0.8 mainly because from the plot it was determined that the value spiked and gave better true positives and less false positives.

The MOPS threshold was much better a descriptor SIFT descriptor because it detects large temporal values as well as different view points, scales and orientations. MOPS was able to return the same exact image as the original image.

The Source Code was Computationally expensive, thus had to resort to comparing these images for a single pair of images to detect the Confusion Matrix. The Source Code was able to detect the features for SIFT and for MOPS but was not able to compute and plot the features.

SOURCE CODE :

```
%% Creating Database of Image, Checkerboard and 5 New Images.
% imageDB{1} = imread('image.bmp');
I = imread('checkerboard.jpg');
I = rgb2gray(I);
n=0;
for i = 0:5:60
    n=n+1;
    imageDB{n} = imrotate(I,i);
    I = double(I);
end
for i = 1:13
    for j = 0:10:30
        n=n+1;
        I = I - min(I(:));
        I = I / max(I(:));
        %/ Add noise to image
        v = var(I(:))/(10^(j/10));
        imageDB{n} = imdse(i imageDB{i}, 'gaussian', 0, v);

    end
end
imageDB{66} = uint8(imread('image1.jpg'));
imageDB{67} = uint8(imread('image2.jpg'));
imageDB{68} = uint8(imread('image3.jpg'));
imageDB{69} = uint8(imread('image4.jpg'));
imageDB{70} = uint8(imread('image5.jpg'));
imageDB{66} = rgb2gray(imageDB{66});
imageDB{67} = rgb2gray(imageDB{67});
imageDB{68} = rgb2gray(imageDB{68});
imageDB{69} = rgb2gray(imageDB{69});
imageDB{70} = rgb2gray(imageDB{70});
n=70;
% for image1.jpg
for i = 0:5:60
    n=n+1;
    imageDB{n} = imrotate(imageDB{66},i);
    imageDB{66} = double(imageDB{66});
end
for i = 71:83
    for j = 0:10:30
        n=n+1;
        imageDB{66} = imageDB{66} - min(imageDB{66}(:));
        imageDB{66} = imageDB{66} / max(imageDB{66}(:));
        %/ Add noise to image
        v = var(imageDB{66}(:))/(10^(j/10));
        imageDB{n} = imdse(imageDB{i}, 'gaussian', 0, v);

    end
end
% For image2.jpg
for i = 0:5:60
    n=n+1;
    imageDB{n} = imrotate(imageDB{67},i);
    imageDB{67} = double(imageDB{67});
end
for i = 136:148
```

```

for j=0: 10: 30
    n=n+1;
    i mageDB{ 67} = i mageDB{ 67} - min(i mageDB{ 67}(:));
    i mageDB{ 67} = i mageDB{ 67} / max(i mageDB{ 67}(:));
    %/ Add noise to i mage
    v = var(i mageDB{ 67}(:))/(10^(j/10));
    i mageDB{ n} = i mnd se(i mageDB{i},'gaussi an', 0, v);

end
end
% For i mage3.jpg
for i = 0: 5: 60
    n=n+1;
    i mageDB{ n}=i mrot at e(i mageDB{ 68},i);
    i mageDB{ 68}=doubl e(i mageDB{ 68});
end
for i=201: 213
    for j=0: 10: 30
        n=n+1;
        i mageDB{ 68} = i mageDB{ 68} - min(i mageDB{ 68}(:));
        i mageDB{ 68} = i mageDB{ 68} / max(i mageDB{ 68}(:));
        %/ Add noise to i mage
        v = var(i mageDB{ 68}(:))/(10^(j/10));
        i mageDB{ n} = i mnd se(i mageDB{i},'gaussi an', 0, v);
    end
end
% For i mage4.jpg
for i = 0: 5: 60
    n=n+1;
    i mageDB{ n}=i mrot at e(i mageDB{ 69},i);
    i mageDB{ 69}=doubl e(i mageDB{ 69});
end
for i=266: 278
    for j=0: 10: 30
        n=n+1;
        i mageDB{ 69} = i mageDB{ 69} - min(i mageDB{ 69}(:));
        i mageDB{ 69} = i mageDB{ 69} / max(i mageDB{ 69}(:));
        %/ Add noise to i mage
        v = var(i mageDB{ 69}(:))/(10^(j/10));
        i mageDB{ n} = i mnd se(i mageDB{i},'gaussi an', 0, v);
    end
end
% For i mage5.jpg
for i = 0: 5: 60
    n=n+1;
    i mageDB{ n}=i mrot at e(i mageDB{ 70},i);
    i mageDB{ 70}=doubl e(i mageDB{ 70});
end
for i=331: 343
    for j=0: 10: 30
        n=n+1;
        i mageDB{ 70} = i mageDB{ 70} - min(i mageDB{ 70}(:));
        i mageDB{ 70} = i mageDB{ 70} / max(i mageDB{ 70}(:));
        %/ Add noise to i mage
        v = var(i mageDB{ 70}(:))/(10^(j/10));
        i mageDB{ n} = i mnd se(i mageDB{i},'gaussi an', 0, v);
    end
end
end

%% Problem 2 ( Harri ss Detect or, Foster ner Harri ss and Adaptive Non Maxi mal Suppression.)
al pha = 0.04; %%constant for foster ner harri s metri c
%%harri s detect or derivative kernel s
har x = [-2,-1, 0, 1, 2];
har y = [-2,-1; 0, 1, 2];
%%3 X3 sobel kernel s
xKern = [-1, 0, 1;-2, 0, 2;-1, 0, 1];
yKern = [-1,-2,-1; 0, 0, 1, 2, 1];
for i=1: 395
    n=n+1;
    xi=zeros(size(i mageDB{i}));
    yi=zeros(size(i mageDB{i}));
    x2=zeros(size(i mageDB{i}));
    xy=zeros(size(i mageDB{i}));
    y2=zeros(size(i mageDB{i}));
    i mageDB{i}=padarray(i mageDB{i}, 5);
    for(j=3: 1: size(i mageDB{i}, 1)-2)

```

```

for(k=3:1:size(imageDB(i),2)-2)
    imageDB(n)(j-2,k-2)=sum(sum([double(imageDB(i)(j,k-2:k+2)).*har x]));
end
end
for(j=3:1:size(imageDB(i),1)-2)
    for(k=3:1:size(imageDB(i),2)-2)
        imageDB(n+1)(j-2,k-2)=sum(sum([double(imageDB(i)(j-2:j+2,j)).*har y]));
    end
end
end
ix2=imread(imageDB(n)).^2;
iy2=imread(imageDB(n+1)).^2;
ixy=ix.*iy;
% x2=gauss(ix2);
% y2=gauss(iy2);
% xiy=gauss(ixiy);
imageDB(n+2)=zeros(size(xiy));

for(j=1:size(x,1))
    for(k=1:size(x,2))
        AC=[x2(j,k),ixy(j,k),iy2(j,k)];
        AC=gauss(AC); %not going to apply a gaussian filter to a 4x4
        imageDB(n+2)(j,k)=det(AC)-d phi*trace(AC)^2;
    end
end

% histogram of histogram = 255; % threshold so it is easier to view

figure();
% show(uint8(imageDB(n+2)))
% title('Forstner-Harris Metric')
a_maxes=zeros(size(imageDB(n+2)));
origmetri c=imread(imageDB(n+2));
imageDB(n+2)=padarray(imageDB(n+2),5);
for(j=3:1:size(imageDB(n+2),1)-2)
    for(q=3:1:size(imageDB(n+2),2)-2)
        neighborhood=imread(imageDB(n+2)(j-1:j+1,q-1:q+1));
        neighborhood=reshape(neighborhood,1,[]);
        neighborhood=sort(neighborhood,'descend');
        if(neighborhood(1)==imageDB(n+2)(i,j))
            a_maxes(j-2,q-2)=neighborhood(1)-neighborhood(2);
        % a_maxes(i-2,j-2)=255;
    end
    a_maxes(j-2,q-2)=0;
end
end
end

loc_maxes=a_maxes;
min_point=sum(a_maxes(:))/nnz(a_maxes);
min_point=min_point^0.4;
a_maxes(a_maxes<=min_point)=0;
a_maxes(a_maxes>min_point)=255;

figure();
% show(uint8(a_maxes))
% title('Local maxes with threshold')

%% adaptive non maximal suppression%%
origmetri c=padarray(origmetri c,5);
q=01;
for j=101:1:size(origmetri c,1)-100
    for k=101:1:size(origmetri c,2)-100
        if loc_maxes(j-100,k-100)==0
            for s=2:1:100
                if checkRadius(q*origmetri c(j,k),j,k,s)
                    imageDB(n+3)(j-100,k-100)=s;
                    break
                else
                    imageDB(n+3)(j-100,k-100)=101;
                end
            end
        end
        a_maxes(j-100,k-100)=0;
    end
end
end
end
end
t_dpx=nnz(imageDB(n+3));

```

```

testit=101;
while (nnz(i mageDB( n+3)) > 9*t d p x)
    i mageDB( n+3)(i mageDB( n+3) >testit) =0;
    for j =1: 1: size(i mageDB( n+3), 1)
        for k=1: 1: size(i mageDB( 3), 2)
            if i mageDB( n+3)(j, k) >testit
                i mageDB( n+3)(j, k) =0;
            end
        end
    end
end
testit =testit -1;
end
i mageDB( n+3)(i mageDB( n+3) ~=0) =255;
end

```

This code was able to create a data base of the 65 images of the various rotated versions and the images with the noise and also images with noise+database.

The code then created 395 images after adding the 5 images and adding noise, and rotating for all the versions.

This made the program initially computationally expensive.

Once this was implemented, the Feature Detection was implemented.

Confusion matrix Code:

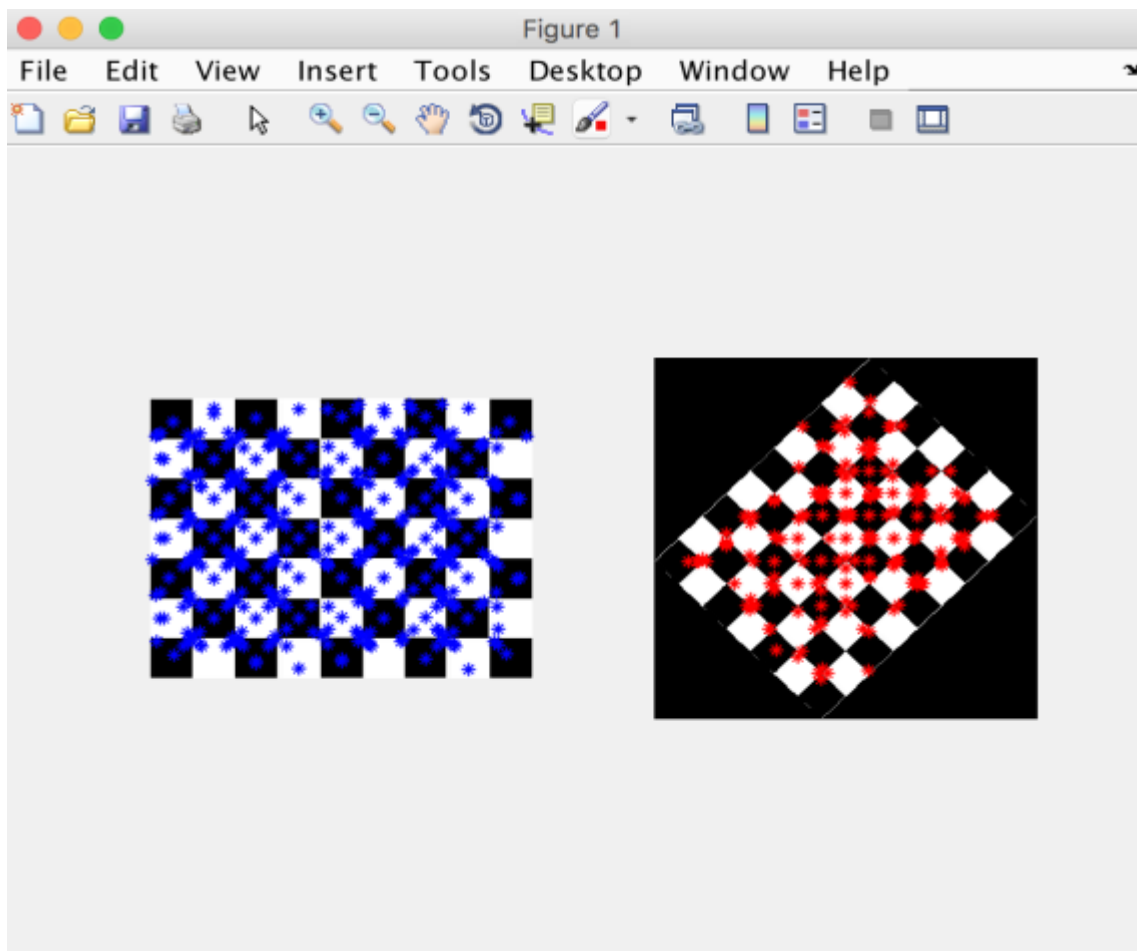
If euclidian distance< threshold

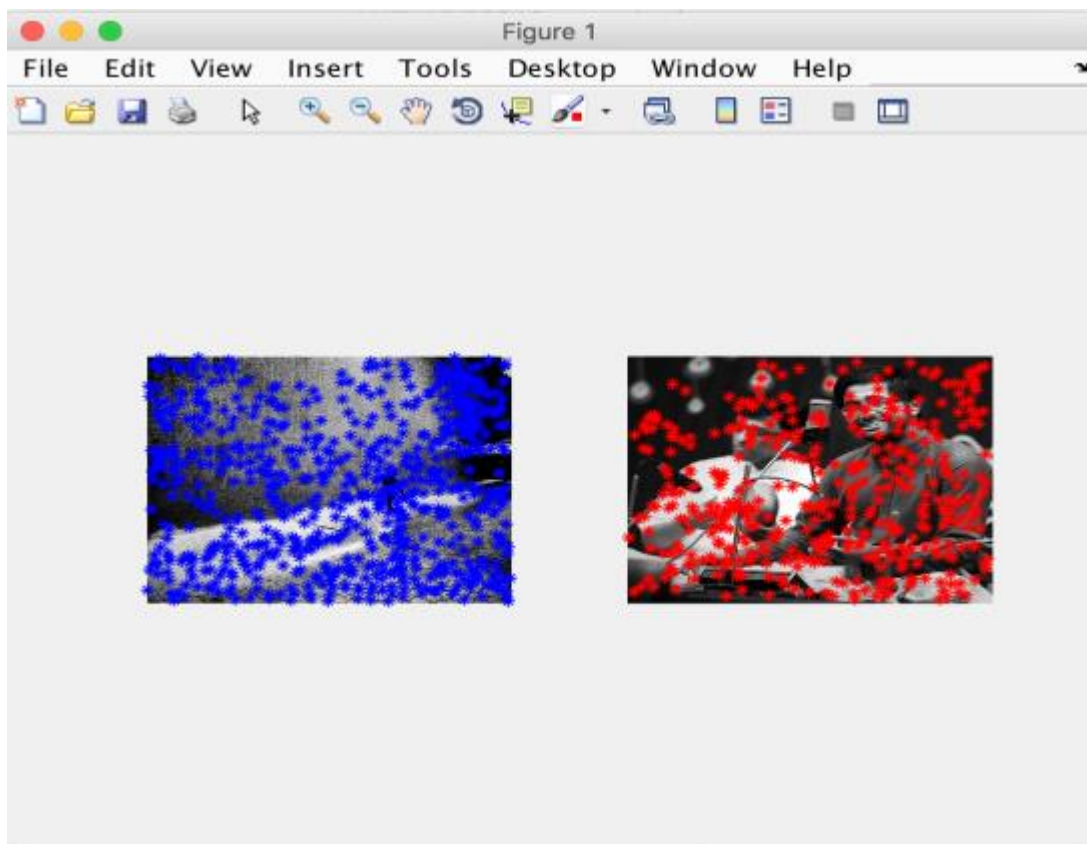
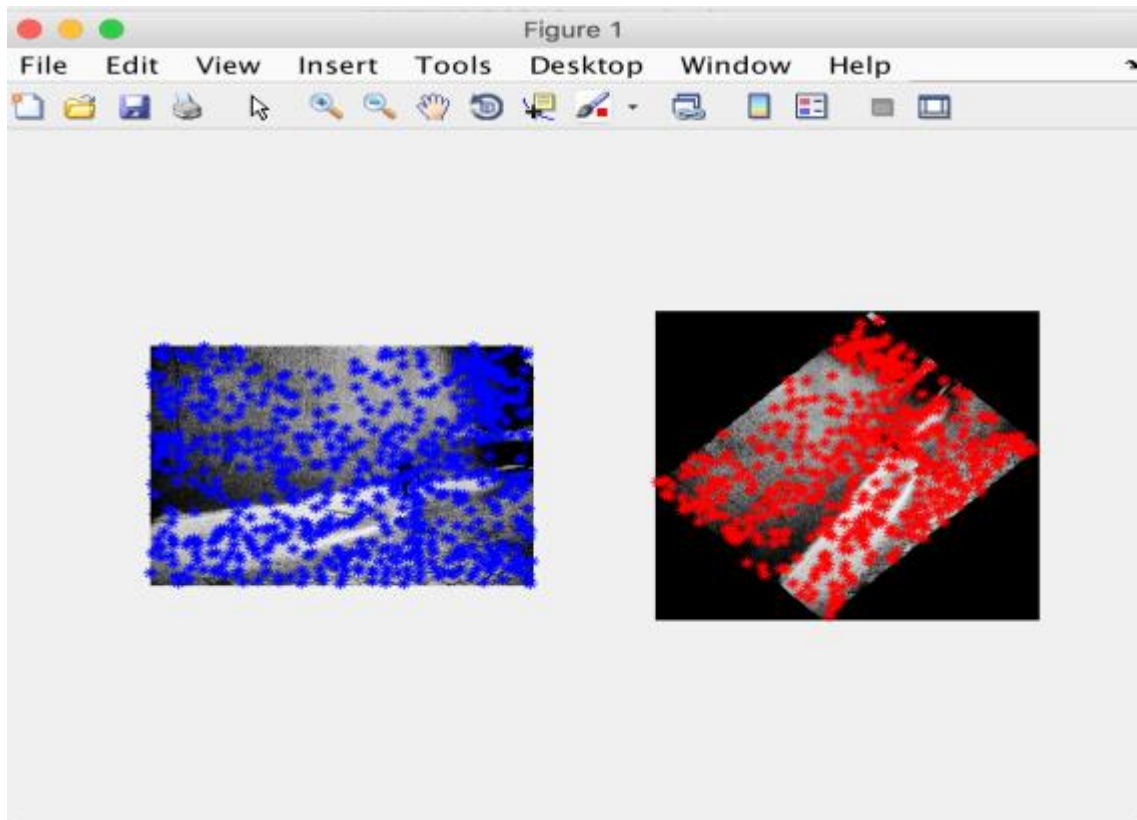
True positive value was returned

Else if euclidian distance? Threshold

False positive value was returned.

SIFT





The above images was obtained on running the SIFT algorithm.

SIFT Algorithm:

```
I = imread('image1.jpg');
J = imread('image3.jpg');

I = single(rgb2gray(I)); % Conversion to single is recommended
J = single(rgb2gray(J)); % in the documentation

[F1 D1] = vl_sift(I);
[F2 D2] = vl_sift(J);

% Where 1.5 = ratio between euclidean distance of NN2/ NN1
[matches score] = vl_ubcmatch(D1, D2, 0.5);

subplot(1, 2, 1);
imshow(uint8(I));
hold on;
plot(F1(1, matches(1,:)), F1(2, matches(1,:)), 'b*');

subplot(1, 2, 2);
imshow(uint8(J));
hold on;
plot(F2(1, matches(2,:)), F2(2, matches(2,:)), 'r*');
```

MOPS Algorithm:

Normalized 8*8 intensity patches were used to detect feature points. The forstner harris metric was applied to this 8*8 matrix which was positioned on every feature that was detected. The kernel used was $1/16[1 \ 4 \ 6 \ 4 \ 1]$. The output was more appealing using MOPS due to its orientational individuality. The orientational patches were spaced at a 5 pixel distance by using image pyramids. That avoided aliasing.

```
b = imgaussfilt(A);
b = imgaussfilt(A);
b = imgaussfilt(A);
b = imgaussfilt(A);
%% constants %%
alpha = 0.04; %% constant for forstner harris metric
%% harris detector derivative kernels
hxKern = [-2, -1, 0, 1, 2];
hyKern = [-2, -1, 0, 1, 2];
%% 3 X 3 sobel kernels
xKern = [-1, 0, 1; -2, 0, 2; -1, 0, 1];
yKern = [-1, -2, -1; 0, 0, 0; 1, 2, 1];

%% blur my image as a preprocessing to make the derivatives nicer %%

%% pad then take the x and y derivatives respectively %%
ix=zeros(size(b));
iy=zeros(size(b));
ix2=zeros(size(b));
ixy=zeros(size(b));
iy2=zeros(size(b));

b=pad(b,'m');
for(i=3:1:size(b,1)-2)
    for(j=3:1:size(b,2)-2)
        ix(i-2,j-2)=sum(sum([double(b(i,j-2:j+2))].*hxKern));
    end
end
for(i=3:1:size(b,1)-2)
    for(j=3:1:size(b,2)-2)
        iy(i-2,j-2)=sum(sum([double(b(i-2:i+2,j))].*hyKern));
    end
end
```

```

    end
end

figure();
imshow(i x);
title('x-derivative')
figure();
imshow(i y);
title('y-derivative')
ix2=i x.^2;
iy2=i y.^2;
ixy=i x.*i y;
ix2=gauss(ix2);
iy2=gauss(iy2);
ixy=gauss(ixy);
fhmetric=zeros(size(i x));

for i=1:1:size(i x,1)
    for j=1:1:size(i x,2)
        AC=[ix2(i,j),ixy(i,j);ixy(i,j),iy2(i,j)];
        %      AC=gauss(AC): %not going to apply a gaussian filter to a 4x4
        fhmetric(i,j)=det(AC)-dpha*trace(AC)^2;
    end
end
end

```