Project 1. Content Based Image Retrieval Using Global and Local Features

Dan Bryan and Olmo Zavala

October 19, 2014

For this project three approaches for Content Based Image Retrieval (CBIR) where implemented. The first approach is based on the comparison of color histograms, the second solution uses spectral histogram to do the comparison of images, and the third approach uses SIFT features to compare images.

1 Description

In this section the three methods used for CBIR are described.

1.1 Color histogram

In this method we used the color (intensity filter) histogram to compare images. The following steps summarizes the method:

1. **Image pyramidization.** The images sizes where reduced to half their size in order to speed up the algorithm. The method used to compute the pyramids is *Gaussian pyramid*, the first step of the Gaussian pyramid algorithm is to blur the image using a Gaussian filter, and then scale down the image by creating one pixel from the average color of four pixels.

2. **Compute histograms.** The number of bins used for this method is 256, for each color band.

3. **Compute histogram distances.** The distance between each pair of image histograms were computed using histogram intersection:

$$dist(hist_a, hist_b) = \sum_{i=1}^{256} \min(hist_a(i), hist_b(i)) \tag{1}$$

4. **Images similarity**. The distance between the histograms of the images was used as the *similarity* parameter.

1.2 Spectral histogram

This method uses spectral histograms for CBIR. The proposed steps for this method are the following:

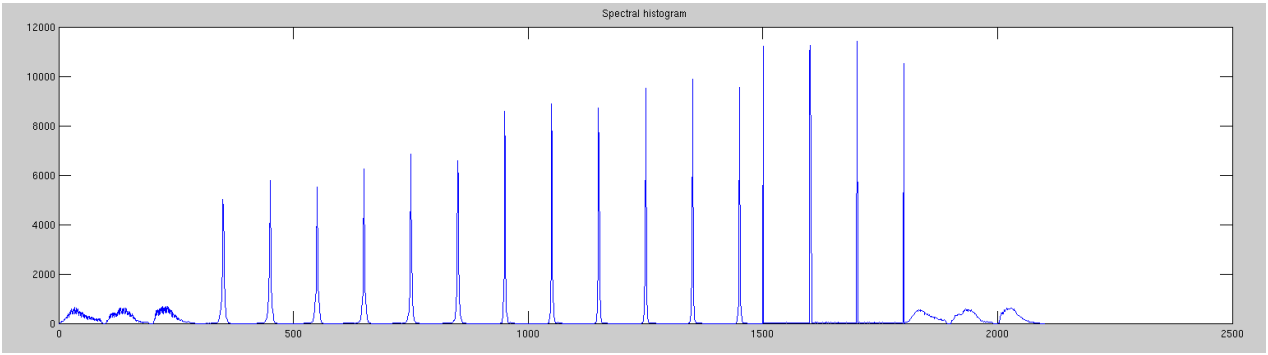
1. **Image pyramidization.** The images sizes where reduced to half their size in order to speed up the algorithm. The method used to compute the pyramids is *Gaussian pyramid*, the first step of the Gaussian pyramid algorithm is to blur the image using a Gaussian filter, and then scale down the image by creating one pixel from the average color of four pixels.

2. **Filter images**. Six filters plus the intensity filter are applied to each of the images. The filters used and their corresponding masks are:

$$\begin{aligned}
\frac{\partial I}{\partial x} &= [0 \ -1 \ 1] \\
\frac{\partial I}{\partial y} &= [0 \ -1 \ 1]^T \\
\frac{\partial I}{\partial x \partial x} &= [-1 \ 2 \ -1] \\
\frac{\partial I}{\partial y \partial y} &= [-1 \ 2 \ -1]^T \\
LoG(I(x,y)) &= (x^2 + y^2 - \sqrt{2\sigma^2}) e^{-(x^2+y^2)/\sqrt{2\sigma^2}} \\
Gauss(I(x,y)) &= \frac{1}{2\pi\sigma^2} e^{\frac{-(x.^2+y.^2)}{2\sigma^2}}
\end{aligned} \tag{2}$$

   For the Laplacian of Gaussian (LoG) and Gaussian filters the size of the filter used is 5 with a sigma value of 0.7.

3. **Compute spectral histograms.** The number of bins used for this method is 100, for each color band and for each filter. For all the filters the range goes from [0 256], even when the values of some of the filters may go from [-256 256]. Several options for the range of the histograms were tested, and the range of [0 256] gave the best results. The 100 bins are evenly split from [0 256]. Figure 3 shows an example of the spectral histograms.



4. **Compute histogram distances.** The distance between each pair of image histograms were computed using histogram intersection:

$$dist(hist_a, hist_b) = \sum_{i=1}^{100} \min(hist_a(i), hist_b(i)) \tag{3}$$

5. **Images similarity**. The distance between the histograms of the images was used as the *similarity* parameter.

1.3 SIFT Features

For this method we use the SIFT descriptors to compare images. The code is based on the implementation provided at `http://www.vlfeat.org/`vlfeat.org. The proposed steps to obtain a score that could be used for CBIR are:

1. Obtain the SIFT descriptors for each image using function **vl_sift**.
2. Compute the matching descriptors and the distance between those descriptors using the function **vl_ubcmatch**.
3. Obtain the maximum distance obtained between all the matches (for later normalization).
4. Combine the average distance of the matched descriptors with the number of matched descriptors between two images using *Cantor pairing*. Equation 4 show the score computed between images i and j using the SIFT features.

$$\begin{aligned} k1 &= mean(\frac{\text{matches}(i,j)}{\text{maxDist}}) \\ k2 &= \text{length}(\text{matches}(i,j)) \text{ \# matched descriptors} \\ \text{siftScore}(i,j) &= (0.5 * (k1 + k2) * (k1 + k2 + 1)) + k2 \end{aligned} \tag{4}$$

1.4 Computation time

The three methods were implemented in parallel (when possible) using the matlab function $parfor$. The third method, which uses SIFT features, takes a lot more time than the others and the computation time is presented separated at the end of this section.

For eficiency, the first two methods are implemented in the same code, but the program *Problem1And2CompTime* can be easily modified to display the time that takes for each method to compute the CBIR. The times shown on table 1.4 are for an specific run in a Laptop computer running Ubuntu 14.04, with matlab 2012a, with an i7 intel processor and 10 GB of ram. The times varies a little for each run but table 1.4 gives a good estimate of the time that each method takes.

	Color histogram (sec)	**Spectral Hist (sec)**
Read Images Filter them and compute histogram	9.38	30.01
Compute distances	6.69	10.78
Compute Precision Recall	1.47	1.45
Avg Precision and Rank	1.22	1.34
Total time	**17.54**	**43.58**

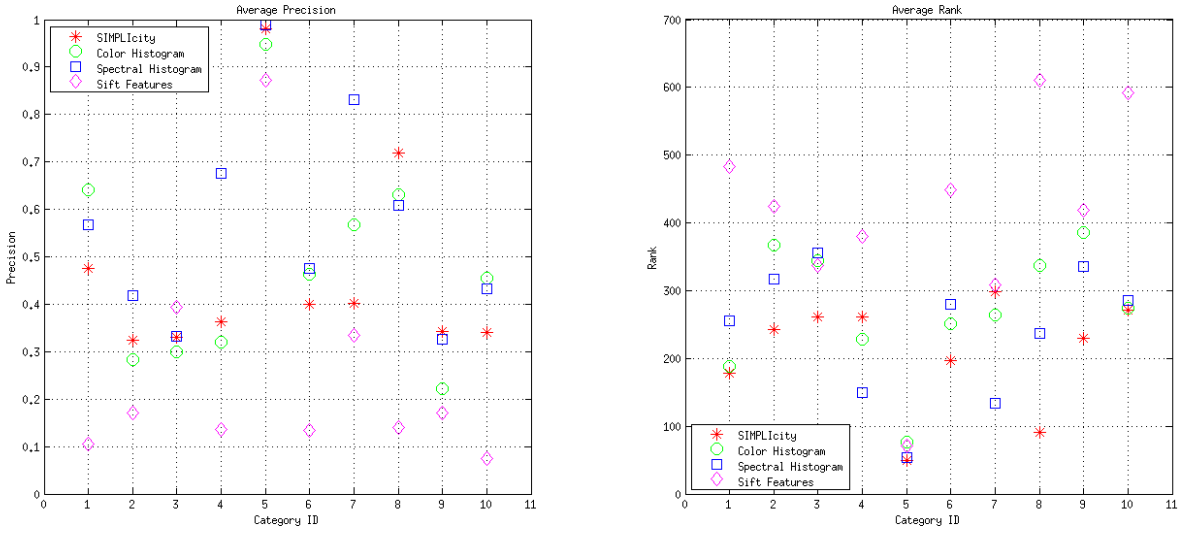
The method based on SIFT features take a lot longer to finish. In order to debug our proposed method, the computation of the SIFT descriptors were run once and then saved in a separated file (*/Variables/descriptors.mat*). In the same way the matching of the descriptors, which takes almost two hours to finish, was also saved in a separated file (*/Variables/scores.mat*). In this way we only had two compute the matching and the descriptors one time. The times shown on table 1.4 are also obtained from a Laptop computer running Ubuntu 14.04, with matlab 2012a, with i7 intel processor and 10 GB of ram. The matching descriptors were also computed using a Desktop pc with i5 Processor, 8 GB of ram in windows 7. For this configuration the average time to calculate each matching descriptor is under 5 seconds and the overall computation time is close to 1 hr.

	SIFT (time sec)
Read all Images	12.47
Detect SIFT descriptors	83.3
Matching descriptors	approx. 7 sec/image $\sim$ 7000 sec $\sim$ 1:56 hrs
SIFT score	18.8
Precision recall	1.6
Average PR	1.44
Total	$\sim$ **2 hrs**

2 Results

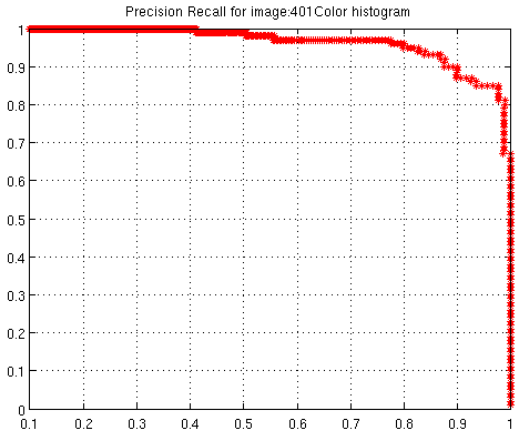
To better compare the results between the proposed method the results are plotted together in figure 2. Figure 2 displays the average precision recall (PR) of the left plot and the average rank on the right. There are four methods analyzed: SIMPLICITY (red star), color histogram (green circle), spectral histogram (blue square), and SIFT features (pink).

The best proposed method is the **Spectral Histogram**, it improves the results shown in the SIMPLICITY paper in 8 of the 10 categories for the average PR and in 2 of the 10 categories for the average image rank. The **Color histogram** method obtain better average PR for some of the categories (1, 8, and 10) but in general is a little bit behind than the Spectral histogram method. The **SIFT** features method seems to over fit the matching of the images and in general obtains poor results. This method is still the only one that surpasses SIMPLICITY for the 5th category in the average PR evaluation. We believe that the problem of the method used compare images based on the SIFT features is that it is not taking into account a 'general' similarity between the descriptors. The function that was used (vl_ubmatch) computes the closest descriptors and their distances, but we don't know if those descriptors were good representation of the original images. A better approach may be to match only the most representative descriptors between the images.



The following are some good and bad examples of the PR obtained for each method in specific images. Figure 2 shows the PR obtained for image #401 for the color histogram and spectral histogram methods. In this case both obtain good PR plots, but the Spectral

histogram method is better.



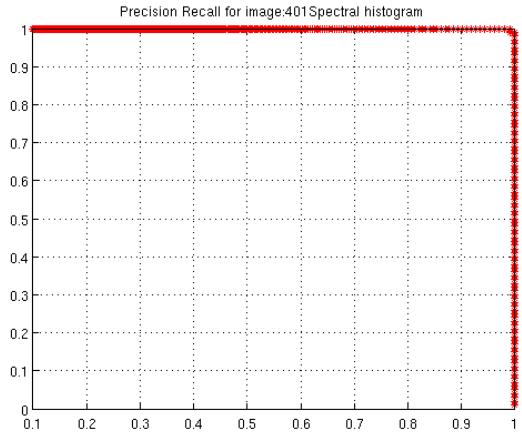
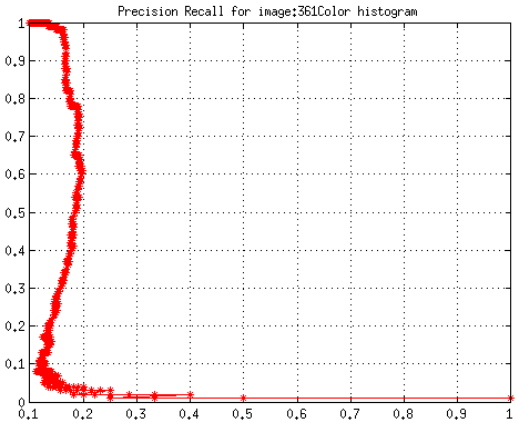
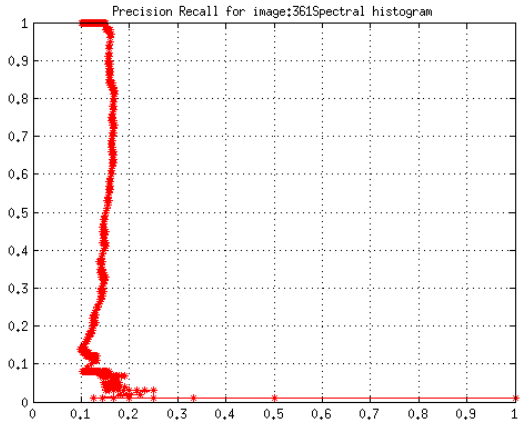
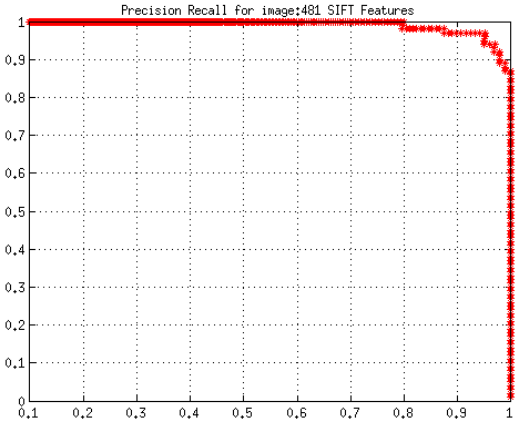


Figure 2 shows the PR obtained for image #361 for Spectral and color histogram. This is an example where the classification is bad. In this example both methods obtain similar results.





Finally, figure 2 shows two PR curves obtained with the SIFT features method. The first case is the image #481 which obtains very good results. This image belongs to the 5th category, which is mostly the only category where SIFT is better than SIMPLICITY. The right plot of figure 2 shows the PR plot for image #331 where it obtains very poor results.



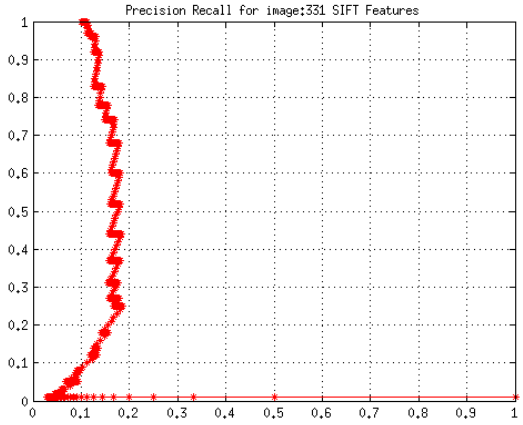


Table of Contents


```
clc;
clear all;
close all;
addpath(genpath('externalLib'));
addpath(genpath('Variables'));

%histograms
totalImages = 1000;

% Running in parallel, check if the pool of threads is already open
if matlabpool('size') == 0
    infoLocal = parcluster('local');
    maxWorkers = infoLocal.NumWorkers;
    matlabpool('open',maxWorkers);
end

bins = [256 100];% Number of bins for each problem (1 and 2)

imgHists = zeros(totalImages, bins(1)*3); % Histograms for problem 1
imgSpectralHists = zeros(totalImages, bins(2)*7*3); % Histograms for problem 2 (us

display('Reading images and computing the histograms....');
tic;
parfor_progress(totalImages);
parfor currIndx =1:totalImages
    % Read images
    fname=sprintf('corel/%i.jpg',currIndx-1);
    currImgInt = imread(fname,'jpg');

    % Reducing size of image
    currImg = double(impyramid(currImgInt,'reduce'));

    [filteredImg numFilters]= filterImages(currImg,3,1);% Filtered image for probl
    %imshow(uint8(squeeze(filteredImg(1,:,:,1))));

    imgHists(currIndx,:) = computeHist(1, currImg, 1, bins(1));
    %plot(imgHists(currIndx,:));
    imgSpectralHists(currIndx,:) = computeHist(1, filteredImg, numFilters, bins(2)
    %plot(imgSpectralHists(currIndx,:));
```

```
    parfor_progress;
end
parfor_progress(0);
toc;
```

```
Warning: Function externalLib/vlfeat/toolbox/noprefix/det.m has the same n
a MATLAB builtin. We suggest you rename the function to avoid a potential
conflict.
Warning: Function externalLib/vlfeat/toolbox/noprefix/det.m has the same n
a MATLAB builtin. We suggest you rename the function to avoid a potential
conflict.
Reading images and computing the histograms....
100%[==================================================]
Elapsed time is 26.167586 seconds.
```

Average precision and rank for Simplicity method for each class

```
simplicityPR=[  0.47477 178.3529;
                0.32446 242.0187;
                0.33027 261.6305;
                0.36296 260.7511;
                0.98117 49.3074;
                0.39964 197.1079;
                0.40218 298.6917;
                0.71858 91.5890;
                0.34188 230.2441;
                0.33971 271.2211 ];
```

Histogram distances for each method

```
for problem=1:3

    switch problem
        case 1 % Color histogram
            hists = imgHists;
            display('Calculating histogram distances');
            dists = computeHistDist(hists,totalImages);
        case 2 % Spectral histogram
            hists = imgSpectralHists;
            display('Calculating histogram distances');
            dists = computeHistDist(hists,totalImages);
        case 3 % Sift features
            dists=sift(totalImages);
    end
    [Y, ind] = sort(-dists);
```

```
    Calculating histogram distances
    100%[==================================================]

    Calculating histogram distances
```

```
100%[==================================================]

Elapsed time is 7.903175 seconds.
Computing our sift score
```

Precision recall[query image, all images, PR]

```
%every image is queried against all totalImages images
tic;
display('Computing precision recall....');
precision_recall = computePrecRecall(totalImages, ind);
toc;
```

```
Computing precision recall....
100%[==================================================]
Elapsed time is 1.299059 seconds.

Computing precision recall....
100%[==================================================]
Elapsed time is 1.126430 seconds.

Computing precision recall....
100%[==================================================]
Elapsed time is 1.425763 seconds.
```

Average precision and rank

```
display('Computing average precision and rank....');
switch problem
    case 1
        imgHistsPR=computeAvgPR(totalImages, ind, precision_recall);
    case 2
        imgSpectralHistsPR=computeAvgPR(totalImages, ind, precision_recall);
    case 3
        siftPR=computeAvgPR(totalImages, ind, precision_recall);
end
```

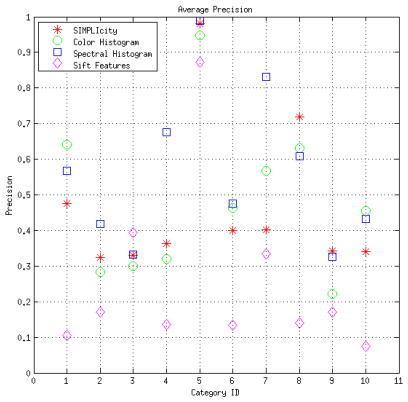
```
Computing average precision and rank....
100%[==================================================]

Computing average precision and rank....
100%[==================================================]

Computing average precision and rank....
100%[==================================================]
```

```
end
```

Plot average precision

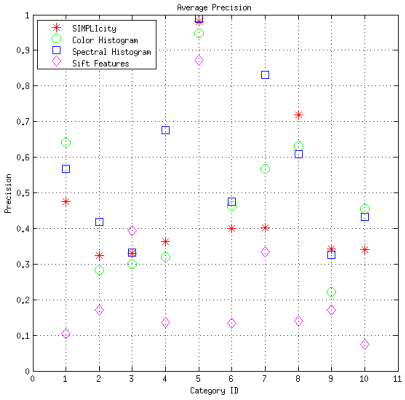
```
figure('Position',[100,100,1500,600])
```

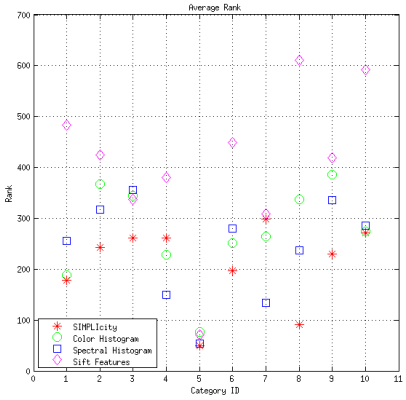
```
subplot(1,2,1);
%Simplicity results
plot(1:10,simplicityPR(:,1),'r*','MarkerSize',10);
hold on
%Our results
plot(1:10,imgHistsPR(:,1),'go','MarkerSize',10);
plot(1:10,imgSpectralHistsPR(:,1),'bs','MarkerSize',10);
plot(1:10,siftPR(:,1),'md','MarkerSize',10);
hold off
title('Average Precision')
xlabel('Category ID');
ylabel('Precision');
legend('SIMPLIcity','Color Histogram','Spectral Histogram','Sift Features');
legend('Location','northwest');
xlim([0,11]);
grid on;
```



Plot average rank

```
subplot(1,2,2);
%Simplicity results
plot(1:10,simplicityPR(:,2),'r*','MarkerSize',10);
hold on
%Our results
plot(1:10,imgHistsPR(:,2),'go','MarkerSize',10);
plot(1:10,imgSpectralHistsPR(:,2),'bs','MarkerSize',10);
plot(1:10,siftPR(:,2),'md','MarkerSize',10);
hold off
title('Average Rank','FontSize',20)
xlabel('Category ID');
ylabel('Rank');
legend('SIMPLIcity','Color Histogram','Spectral Histogram','Sift Features');
legend('Location','southwest');
xlim([0,11]);
grid on;
```





Published with MATLAB® 7.14

Table of Contents


```
function siftScore = sift(totalImages)
```

Calculate descriptors for images

```
tic;
if exist('Variables/descriptors.mat', 'file')
    load('descriptors.mat','descriptors');
else
    display('Detecting SIFT features and descriptors...');
    parfor_progress(totalImages);
    for i=1:totalImages
        [fa, descriptors{i}] = vl_sift(single(rgb2gray(uint8(squeeze(origImages(i,
        parfor_progress;
    end
    save('Variables/descriptors.mat','descriptors');
end
```

Compare descriptors to determine scores

```
if exist('Variables/scores.mat', 'file')
    load('scores.mat','score');
else
    display('Computing Scores...');
    for i=1:totalImages
        tic;
        parfor j=1:totalImages
            [matches, scores{i,j}] = vl_ubcmatch(descriptors{i}, descriptors{j});
        end
        fprintf('%d of 1000: %c',i);
        toc;
    end
    save('Variables/scores.mat','scores');
end
scores = score;
clear score;
toc;
```

Obtaining finalScore

```
% Obtaining max distance
maxDist = 0;
for i=1:totalImages
```

```
    for j=1:totalImages
        currMax = max(scores{i,j});
        if(currMax > maxDist)
            maxDist = currMax;
        end
    end
end

display('Computing our sift score');
siftScore = zeros(totalImages,totalImages);
parfor i=1:totalImages
    for j=1:totalImages
        % Utilize Cantor pairing to ensure one to one mapping for
        % number of matched descriptors with their average
        % distance(Euclidean)
        k1=round(mean(scores{i,j})/maxDist);
        k2=length(scores{i,j});
        siftScore(i,j) = (0.5*(k1+k2)*(k1+k2+1))+k2;
    end
end

end
```

Published with MATLAB® 7.14

```
% The parameter option indicates which filters are we using.
function [filteredImg numFilters] = filterImages(images, option, totalImages)
    switch option
        case 1 %No filters (just the intensity filter)
            filteredImg = images;
            numFilters = 1;
        case 2 % Using just GaussMask
            kernelSize = 5;
            sigma = 0.7;
            filteredImg = zeros(size(images));
            numFilters = 1;
            gaussMask = oz_gaussMask(kernelSize, sigma);
            parfor_progress(length(images));
            for i=1:length(images)
                filteredImg(i,:,:,1) = conv2(squeeze(images(i,:,:,1)),gaussMask, '
                filteredImg(i,:,:,2) = conv2(squeeze(images(i,:,:,2)),gaussMask, '
                filteredImg(i,:,:,3) = conv2(squeeze(images(i,:,:,3)),gaussMask, '
                parfor_progress;
            end
            parfor_progress(0);
            % If you want to visualize any (i) of the filtered images use:
            %imshow(uint8(squeeze(filteredImg(i,:,:,3)))); % 3 is the band of the
        case 3 % Using the 4 filters from the paper
            dimsImages = size(images);
            numFilters = 7;

            if(totalImages > 1) % We have more than one image
                filteredImg = zeros(dimsImages(1)*numFilters, dimsImages(2), dimsI
            else
                filteredImg = zeros(numFilters, dimsImages(1), dimsImages(2), dims
            end

            kernelSize = 5;
            sigma = 0.7;

            theta = 0;
            gabor = gaborFilter(kernelSize, sigma, theta);

            dx = [0 -1 1]; % Range [-256 256]
            dy = [0 -1 1]'; % Range [-256 256]
            dxx = [-1 2 -1];% Range [-512 512]
            dyy = [-1 2 -1]';% Range [-512 512]
            maskLoG = maskLoGFunc(kernelSize, sigma);% Range ?
            gaussMask = oz_gaussMask(kernelSize, sigma);% Range [0 256]

            if(totalImages > 1) % We have more than one image
                parfor_progress(totalImages);
                for i=0:totalImages-1
                    % First filter is the intensity filter
                    filteredImg(i*numFilters+1,:,:,1) = images(i+1,:,:,1);
                    filteredImg(i*numFilters+1,:,:,2) = images(i+1,:,:,2);
                    filteredImg(i*numFilters+1,:,:,3) = images(i+1,:,:,3);
```

```
            % Second filter is dx
            filteredImg(i*numFilters+2,:,:,1) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+2,:,:,2) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+2,:,:,3) = conv2(squeeze(images(i+1,:
            % Third filter is dy
            filteredImg(i*numFilters+3,:,:,1) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+3,:,:,2) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+3,:,:,3) = conv2(squeeze(images(i+1,:
            % Fordth filter is dxx
            filteredImg(i*numFilters+4,:,:,1) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+4,:,:,2) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+4,:,:,3) = conv2(squeeze(images(i+1,:
            % Fifth filter is dxx
            filteredImg(i*numFilters+5,:,:,1) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+5,:,:,2) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+5,:,:,3) = conv2(squeeze(images(i+1,:
            % Sixth filter is LoG
            filteredImg(i*numFilters+6,:,:,1) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+6,:,:,2) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+6,:,:,3) = conv2(squeeze(images(i+1,:
            % Seventh filter is Gauss
            filteredImg(i*numFilters+7,:,:,1) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+7,:,:,2) = conv2(squeeze(images(i+1,:
            filteredImg(i*numFilters+7,:,:,3) = conv2(squeeze(images(i+1,:
            parfor_progress;
        end
        parfor_progress(0);
    else
        % First filter is the intensity filter
        filteredImg(1,:,:,1) = images(:,:,1);
        filteredImg(1,:,:,2) = images(:,:,2);
        filteredImg(1,:,:,3) = images(:,:,3);
        % Second filter is dx
        filteredImg(2,:,:,1) = conv2(images(:,:,1),dx, 'same');
        filteredImg(2,:,:,2) = conv2(images(:,:,2),dx, 'same');
        filteredImg(2,:,:,3) = conv2(images(:,:,3),dx, 'same');
        % Third filter is dy
        filteredImg(3,:,:,1) = conv2(images(:,:,1),dy, 'same');
        filteredImg(3,:,:,2) = conv2(images(:,:,2),dy, 'same');
        filteredImg(3,:,:,3) = conv2(images(:,:,3),dy, 'same');
        % Fordth filter is dxx
        filteredImg(4,:,:,1) = conv2(images(:,:,1),dxx, 'same');
        filteredImg(4,:,:,2) = conv2(images(:,:,2),dxx, 'same');
        filteredImg(4,:,:,3) = conv2(images(:,:,3),dxx, 'same');
        %min(min(filteredImg(i*numFilters+4,:,:,3)))
        %max(max(filteredImg(i*numFilters+4,:,:,3)))
        % Fifth filter is dxx
        filteredImg(5,:,:,1) = conv2(images(:,:,1),dyy, 'same');
        filteredImg(5,:,:,2) = conv2(images(:,:,2),dyy, 'same');
        filteredImg(5,:,:,3) = conv2(images(:,:,3),dyy, 'same');
        % Sixth filter is LoG
        filteredImg(6,:,:,1) = conv2(images(:,:,1),maskLoG, 'same');
        filteredImg(6,:,:,2) = conv2(images(:,:,2),maskLoG, 'same');
        filteredImg(6,:,:,3) = conv2(images(:,:,3),maskLoG, 'same');
```

```
            % Seventh filter is Gauss
            filteredImg(7,:,:,1) = conv2(images(:,:,1),gaussMask, 'same');
            filteredImg(7,:,:,2) = conv2(images(:,:,2),gaussMask, 'same');
            filteredImg(7,:,:,3) = conv2(images(:,:,3),gaussMask, 'same');
        end

    case 4 % Intensity and Gauss
        dimsImages = size(images);
        numFilters = 2;

        filteredImg = zeros(dimsImages(1)*numFilters, dimsImages(2), dimsImage
        kernelSize = 5;
        sigma = 0.7;

        gaussMask = oz_gaussMask(kernelSize, sigma);% Range [0 256]

        % TODO missing Gabor filter
        parfor_progress(length(images));
        for i=0:length(images)-1
            % First filter is the intensity filter
            filteredImg(i*numFilters+1,:,:,1) = images(i+1,:,:,1);
            filteredImg(i*numFilters+1,:,:,2) = images(i+1,:,:,2);
            filteredImg(i*numFilters+1,:,:,3) = images(i+1,:,:,3);
            %min(min(filteredImg(i*numFilters+1,:,:,3)))
            %max(max(filteredImg(i*numFilters+1,:,:,3)))
            % Second filter is dx
            %filteredImg(i*numFilters+2,:,:,1) = images(i+1,:,:,1);
            %filteredImg(i*numFilters+2,:,:,2) = images(i+1,:,:,2);
            %filteredImg(i*numFilters+2,:,:,3) = images(i+1,:,:,3);
            % Second filter is dx
            filteredImg(i*numFilters+2,:,:,1) = conv2(squeeze(images(i+1,:,:,1
            filteredImg(i*numFilters+2,:,:,2) = conv2(squeeze(images(i+1,:,:,2
            filteredImg(i*numFilters+2,:,:,3) = conv2(squeeze(images(i+1,:,:,3
            %min(min(filteredImg(i*numFilters+4,:,:,3)))
            %max(max(filteredImg(i*numFilters+4,:,:,3)))
            parfor_progress;
        end
        parfor_progress(0);

        % If you want to visualize any (i) of the filtered images use:
        %imshow(uint8(squeeze(filteredImg(i,:,:,3)))); % 3 is the band of the
    end
```

Published with MATLAB® 7.14

```
function hists = computeHist(totalImages, images, numFilters,bins)

    hists=zeros([totalImages,bins*3*numFilters]);%One filter for each band

    if(totalImages>1 || numFilters>1) % We have more than one image
        totRows = size(images(1,:,:,:),2);
        totCols = size(images(1,:,:,:),3);
    else
        totRows = size(images,1);
        totCols = size(images,2);
    end

    minRange = 0;
    maxRange = 256;
    histRange = [minRange:(maxRange-minRange)/(bins-1):maxRange];
    tempSpectralHist = zeros(3*bins*numFilters,1);
    for i=0:totalImages-1
        for j=0:numFilters-1
            % Modifying the range depending on the filter used (it didn't help)
            switch j
                case 0
                    minRange = 0;
                    maxRange = 256;
                case 1
                    minRange = -256;
                    maxRange = 256;
                case 2
                    minRange = -256;
                    maxRange = 256;
                case 3
                    minRange = -512;
                    maxRange = 512;
                case 4
                    minRange = -512;
                    maxRange = 512;
                case 5
                    minRange = 0;
                    maxRange = 256;
                case 6
                    minRange = 0;
                    maxRange = 256;
                case 1
            end

            histRange = [minRange:(maxRange-minRange)/(bins-1):maxRange];

            if(totalImages>1 || numFilters>1) % We have more than one image
                im = images(i*numFilters+1+j,:,:,:);
                im = squeeze(im);%Remove the first 'simgle' dimension
            else
                im = images;
            end
```

```
            % ---- Using bins ---------
            %tempSpectralHist(j*bins*3+1:j*bins*3+bins) = hist(reshape(im(:,:,1),[
            %tempSpectralHist(j*bins*3+bins+1:j*bins*3+2*bins) = hist(reshape(im(:
            %tempSpectralHist(j*bins*3+2*bins+1:j*bins*3+3*bins) = hist(reshape(im

            % ---- Using ranges ---------
            tempSpectralHist(j*bins*3+1:j*bins*3+bins) = hist(reshape(im(:,:,1),[1
            tempSpectralHist(j*bins*3+bins+1:j*bins*3+2*bins) = hist(reshape(im(:,
            tempSpectralHist(j*bins*3+2*bins+1:j*bins*3+3*bins) = hist(reshape(im(
        end

        if(totalImages>1) % We have more than one image
            hists(i+1,:)= tempSpectralHist;
        else
            hists= tempSpectralHist;
        end
    end
```

Published with MATLAB® 7.14

```
function dists = computeHistDist(hists,totalImages)

    parfor_progress(totalImages);% External library Copyright (c) 2011, Jeremy Sch
    dists=zeros([totalImages,totalImages]);
    parfor i=1:totalImages
        parfor_progress;
        for j=1:totalImages
            dists(i,j)=sum(min(hists(i,:),hists(j,:)));
        end
    end
    parfor_progress(0);
```

Published with MATLAB® 7.14

This function creates a Gaussian mask of nxn

```
function gauss2d = maskLoGFunc(n,sigma)

T = sqrt(2)*sigma;
f = @(x,y,sigma) ( x.^2 + y.^2 - T.^2 ) .* exp( -(x.^2+y.^2)/T^2 );

width = 5;
height = 5;
x = [-width/2:width/n:width/2];
y = [-height/2:height/n:height/2];

[X,Y] = meshgrid(x,y);

gauss2d= f(X,Y,sigma);

%Normalization of the gauss function
total = sum(sum(gauss2d));
gauss2d = gauss2d./total;%It doens't validate that the minimum can be 0

%surf(gauss2d);
```

Published with MATLAB® 7.14

```
function images = readImages(totalImages, imgPath)

    % Read one image and obtain the dimensions
    fname=sprintf('%s/%i.jpg',imgPath,0);
    tempImg = double(imread(fname,'jpg'));
    dim = size(tempImg);
    images = zeros(totalImages, dim(1), dim(2), dim(3));
    parfor_progress(totalImages);
    for i=1:totalImages
        fname=sprintf('%s/%i.jpg',imgPath,i-1);
        clear tempImg;
        tempImg = imread(fname,'jpg');
        if( size(tempImg,1) ~= dim(1) ) %The image is rotated
            images(i,:,:,1)= tempImg(:,:,1)';
            images(i,:,:,2)= tempImg(:,:,2)';
            images(i,:,:,3)= tempImg(:,:,3)';
        else
            images(i,:,:,:)= tempImg;
        end
        parfor_progress;
    end
    parfor_progress(0);
```

Published with MATLAB® 7.14