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Blur Image Estimation in the Frequency Domain by using Image Quality Index

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ABSTRACT

Image blur occurs often when using a camera due to handshake or jitter. Although there exist many motion de-blurring algorithms in the literature, the computational complexities of these algorithms and the assumptions considered make them unsuitable for deployment on a cell-phone camera processor. This project presents a new reference-free image quality index based on spectral analysis is proposed. The main idea is based on exploiting the limitations of the Human Visual System (HVS) in blur detection; the proposed method consists of adding blur to the test image and measuring its impact. The impact is measured using radial analysis in the frequency domain. The efficiency of the proposed method is tested objectively by comparing it to some well known algorithms and in terms of correlation with subjective scores.

Key words: *Blur estimation, Fourier analysis, Subjective tests.*

I. INTRODUCTION

When a photograph is taken in low light conditions or of a fast moving object, motion blur can cause significant degradation of the image. This is caused by the movement of the object relative to the sensor in the camera during the time the shutter is open. Both the object moving and camera shake contribute to this blurring. The problem is particularly apparent in low light conditions when the exposure time can often be in the region of several seconds. There are several techniques for either preventing image motion blurring at the time of image capture or
Post processing images to remove motion blur. As well as in every day photography, the problem is particularly important to applications such as video surveillance where low quality cameras are used to capture sequences of photographs of moving objects (usually people).

Current techniques can be split roughly into the following categories:

- Hardware in the optical system of the camera to stabilize the image
- Post processing of the image to remove motion blur by estimating the camera's motion
- From a single photograph (blind de-convolution)
- From a sequence of photographs
- A hybrid approach that measures the camera's motion during photograph capture.

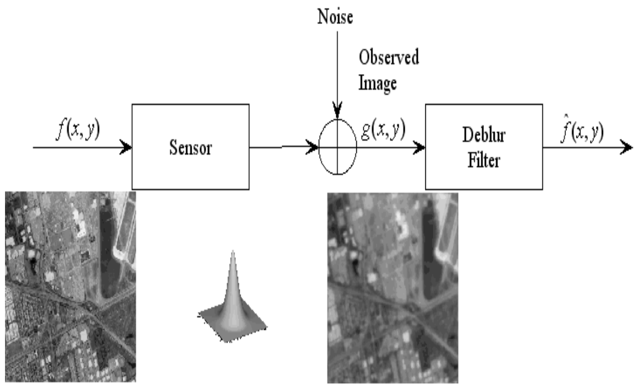
Image quality assessment plays nowadays an important role in various multimedia applications. This research carried in area has reached a certain level of maturity in the multimedia communications community. Several image quality metrics have been proposed in the literature [I. Avcibas et al., 2002]. Unfortunately, in the absence of a universal image quality index, people still continue to use the classical PSNR (Peak Signal to Noise Ratio) in many applications. Moreover, the problem of finding the best image quality index becomes more challenging when various types distortions are considered. As such, many of the researchers continue to propose new heuristic metrics based on psychophysical tests and some established databases. The intend of this work is not to propose a quality index for all the known distortions but rather to focus on a particular artifact, namely blurring. This artifact mostly affects salient features such as contours and can result in drastic quality degradation. The fine details lost due to the blur correspond to the high frequencies in the image. This phenomenon is commonly found in compression applications in which high frequency components are generally neglected. We will discuss in what follows a number of techniques used in estimating blur, then we present our own approach and discuss how it is used in developing the Image quality index(IQI). can be derived from the basic image parameters: contrast, MTF, Wiener spectrum. Several evaluation methods of the IQI, all based on statistical decision theory, have been considered. An experimental visibility test using simulated micro calcifications has been performed in order to compare the results obtained with different IQI models. A previous approach, based on simplifying assumptions, yields a good correlation with the visibility test but fails to predict the actual size of the visible objects. Improved models have been derived for an ideal observer and for a 'quasi-ideal' one with perfect or with realistic visual characteristics. The experimental visual results are well modeled by the IQI method.

II. PREVIOUS WORK

In [H. Tong et al., 2004] a blur estimation method based on wavelets was proposed. An edge map is obtained after combining the coefficients of high frequencies of each decomposition level. The blur measure is then obtained by analyzing the type of the edge contained in the image.
In [X. Marichal et al., 1999], a no reference blur estimation method based on DCT is proposed. First, a block-wise DCT transform is applied to the image. By comparing the DCT coefficients inside each block 8x8 to some thresholds, a global blur measure is then derived. In [J. Caviedes et al., 2004] the DCT is used to estimate the blur without a reference image. The idea is to measure the peakedness of each block 8x8 around each edge point by computing the kurtosis coefficient. Then, the kurtosis coefficient is computed in each block. The mean value of the kurtosis coefficients is then used as a global measure of the blur.
In this work, we propose a new blur estimation inspired by the idea developed in [F. Crete et al., 2007]. It is worth noting that since blurring affects mainly object contours, most blur estimation algorithms are based primarily on edge detection. However, in the case of highly blurred images, edge detection fails resulting in poor estimation of the blurring artifact. Here, we adopt another approach without referring to edge detection. The idea is to add blur to the distorted image and analyze its impact on the image quality. A radial analysis in the frequency domain is applied to both the distorted image and its filtered version. A Blur Index (BI) is then computed from this radial analysis.
The paper is organized as follows: Section 2 describes in details the proposed method. Section 3 is dedicated to the objective and subjective evaluations of the proposed method. Finally, some concluding remarks are discussed in the last section.

III. IMAGE BLUR MODEL

Image blur is a common problem. It may be due to the point spread function of the sensor, sensor motion, or other reasons.



Linear model of observation system is given as
g(x, y) = f(x, y) ? h(x, y) +_(x, y)

Causes of Blurring

The blurring, or degradation, of an image can be caused by many factors:

1. Movement during the image capture process, by the camera or, when long exposure times are used, by the subject.
2. Out-of-focus optics, use of a wide-angle lens, atmospheric turbulence, or a short exposure time, which reduces the number of photons captured.
3. Scattered light distortion in confocal microscopy.

Negative Effects of Motion Blur

In televised sports where conventional cameras expose pictures 25 or 30 times per second, motion blur can be inconvenient because it obscures the exact position of a projectile or athlete in slow motion .For this reason special cameras are often used which eliminate motion blurring by taking rapid exposures on the order of 1/1000 of a second, and then transmitting them over the course of the next 1/25 or 1/30 of a second. Although this gives sharper slow motion replays it can look strange at normal speed because the eye expects to see motion blurring and does not. Sometimes, motion blur can be removed from images with the help of deconvolution.

IV. THE PROPOSED METHOD

We propose to estimate the blurring effect by first adding blur to the test image, then analyzing its effect. Figure 1 displays three images with different levels of blur. One can note that the human perception of blur depends upon the original image ”blurriness” level of the original image. In figure 1, the application of a first blur yields the image displayed in Fig. 1.b whereas Fig. 1.c is the application of a second blur to image in Fig. 1b, using the same filter.
We can see that the perceptual difference is more visible between the images in Fig. 1.a and Fig. 1.b than the images Fig. 1.b and Fig. 1.c in spite of having used the same filtering strength. Therefore, the perceived HVS estimation of blur is not monotonic. Also we can note that

the impact of the blurring for a given image depends on the original image quality level, i.e. sharpness/blur strength. In other words, the blur effect on an already blurred image has less perceptual impact than on a sharpened image.

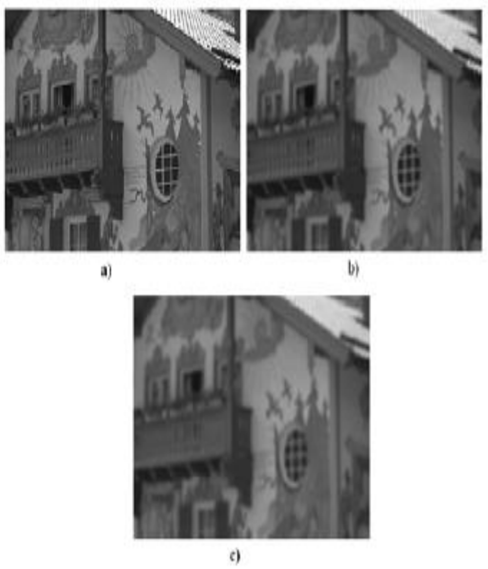


Fig. 1: a) Original image, b) Filtered image with a 3x3 binomial filter and c) Result of applying the same filter to the filtered image with a 3x3 binomial filter

In order to better visualize this effect, we consider a 2D random test signal. We analyze the energy spectrum of this signal and the result of applying a 3x3 binomial filter repeatedly, first to the original signal and then to this filtered version. The energy spectrum of the original and the filtered signals are displayed on Fig. 2. It could be noticed that the filter impact is effectively less visible on the energy spectrum as shown in Fig. 2b and Fig. 2c. Based on the above observations, we propose to exploit this characteristic of the HVS to evaluate the blur in an image by applying a blurring operation, then analyzing the impact of this degradation to quantify the quality of the original image. After transforming both the original and the blurred images into the frequency domain, we apply a radial analysis and deduce a Blur Quality Index [A. Beghdadi et al., 2000]. The flowchart of the proposed algorithm is illustrated in figure 3.

The first step consists of adding blur to the degraded image.We propose to simulate the blur with a 3x3 binomial filter.Figure 4 shows an example of a test image. Figs. 4.a and 4.b show a real image and its degraded version, respectively. A zoomed zone taken from the original and filtered images is displayed in Fig. 4.c and Fig. 4.d.

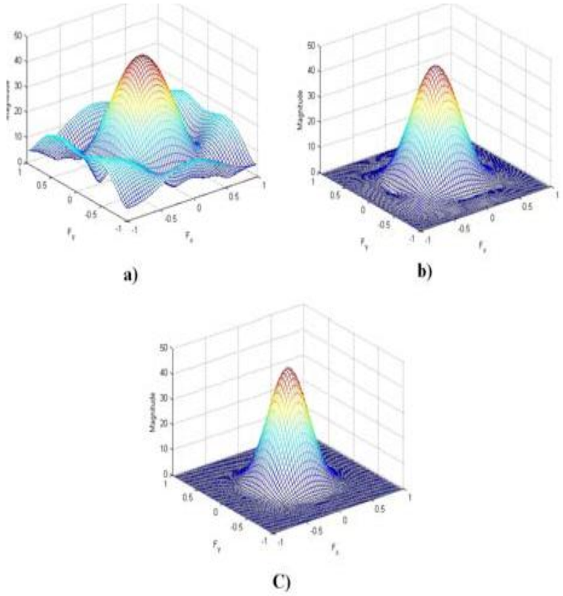


Fig. 2. a) Energy spectrum of the original signal, b) Energy spectrum of the filtered signal c) Energy spectrum of the refiltered signal

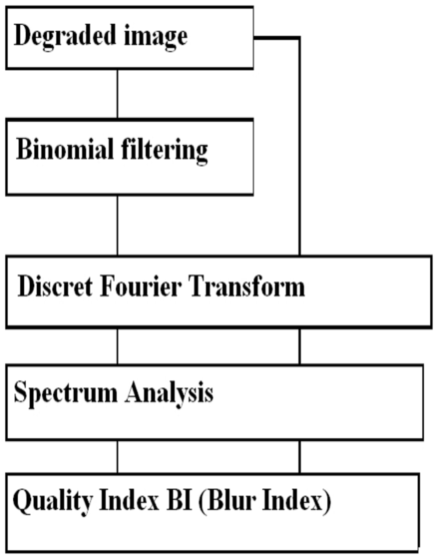


Figure 3: Flowchart of the proposed method

Once the test image and its filtered version are obtained, the discrete Fourier transform of the two images is computed using the following equation:

$$F(u,v) = \frac{1}{XY}\sum_{X}\sum_{Y} f(x,y).(-1)^{x+y}.e^{-2j\Pi(\frac{ux}{X}+\frac{vy}{Y})}$$

Where F(u,v) represent the centered Fourier coefficients corresponding the image f(x,y). (X,Y) represent the size of the image and (u,v) are the spatial frequencies.

V. SIMULATIO RESULT

Source code for Main Program:

```
*************************************************
****************************
clc;
clear all;
close all;
I=uigetfile('.jpg','select the image');
I=imread(I);
I=imresize(I,[256 256]);
if size(I,3)~=3
   error('Input Invalid:Please enter a color image');
else
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%
%%% here we are supposed to apply a 3x3 binomial filter
figure,imshow(I);title('Original image');
I=im2double(I);
for k=1:size(I,3)
%%%% step1 Apply Binomial filte of 3x3 size
mm=filt_binomial(3,3);
dimg(:,:,k)=imfilter(I(:,:,k),mm);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
%%%% Step2 again the same filter for the degraded
image
bimg(:,:,k)=imfilter(dimg(:,:,k),mm);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
%%% calculate the FFT for test and filterd images %%%
Ft=fft2(I(:,:,k));
Ff=fft2(bimg(:,:,k));
for i=1:length(Ft)
   for j=1:length(Ft)
      ER(i,j)=abs(cart2pol(imag(Ft(i,j)),real(Ft(i,j))));
     ERf(i,j)=abs(cart2pol(imag(Ff(i,j)),real(Ff(i,j))));
   end
end
%%%% calculate the BI %%%%
wmax=max(max(ER));
BI(:,:,k)=log((1/wmax)*sum(sum(abs(ER-ERf))));
end
figure,imshow(dimg);title('Degraded image');
figure,imshow(bimg);title('Blurred image');
bb=(BI(:,:,1)+BI(:,:,2)+BI(:,:,3))/3;
disp(['The Blur Index of the image is ',num2str(bb)])
end
*******************************
```

The following Source code for Binomial filtering

```
************************************
function f = filt_binomial(m, n, d)
% filt_binomial - create binomial filters
% --------------------------------------
% Input:
% ------
%  m - row length of filter
%  n - column length of filter
%  d - derivative indicator
% Output:
% -------
%  f - binomial filter
 if (nargin < 3)
   d = [0, 0];
end
 if (nargin < 2)
   n = 1;
end
 if (m < 1) || (n < 1)
  error('Length of filter must be larger than or equal to 1');
end
 %------------------------------
% CREATE FILTER
%------------------------------
% create filter and normalize
f = binomial(m, d(1)) * binomial(n, d(2))';
f = f ./ sum(abs(f(:)));
%------------------------------
% BINOMIAL
%------------------------------
function f = binomial(m, d)
% create column filter
f = 1;
for k = 1:(m - 1)
   f = conv([0.5 0.5]', f);
end
% compute derivative if needed
if d
   ix = length(f) / 2;
   if mod(length(f), 2)
      ix = floor(ix); f = f(1:ix); f = [-f; 0; flipud(f)];
   else
      f = f(1:ix); f = [-f; flipud(f)];
   end
end
```

The following **figures a) and b)** are used for simulation Results:

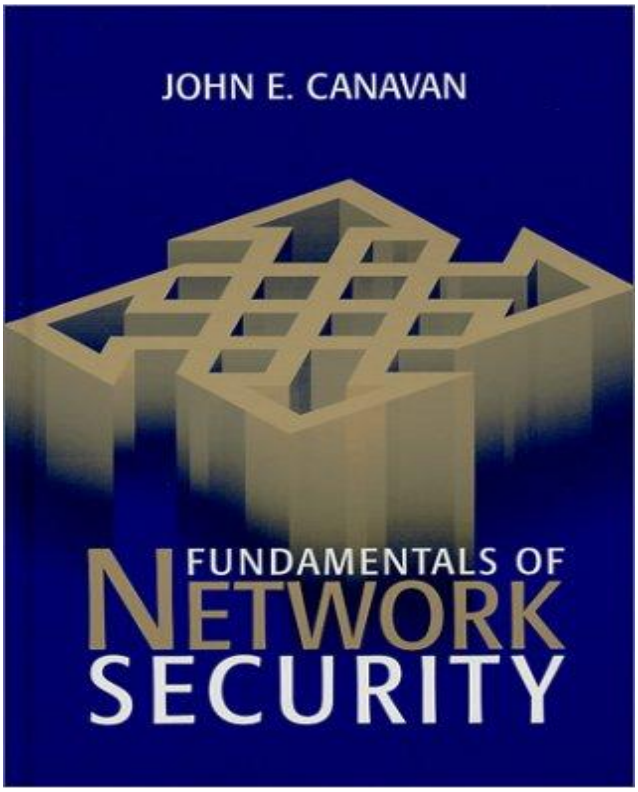
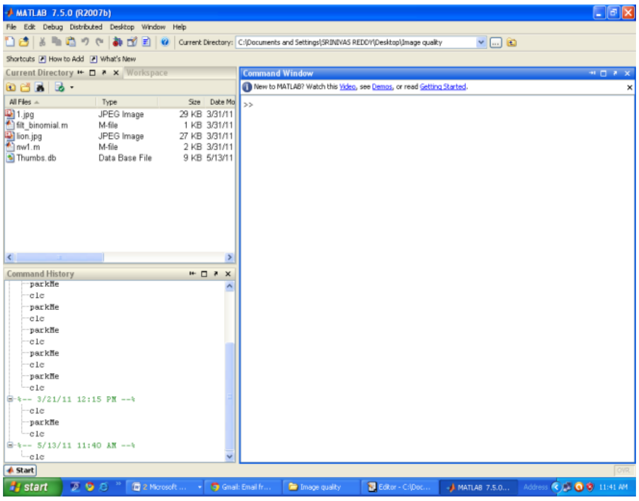


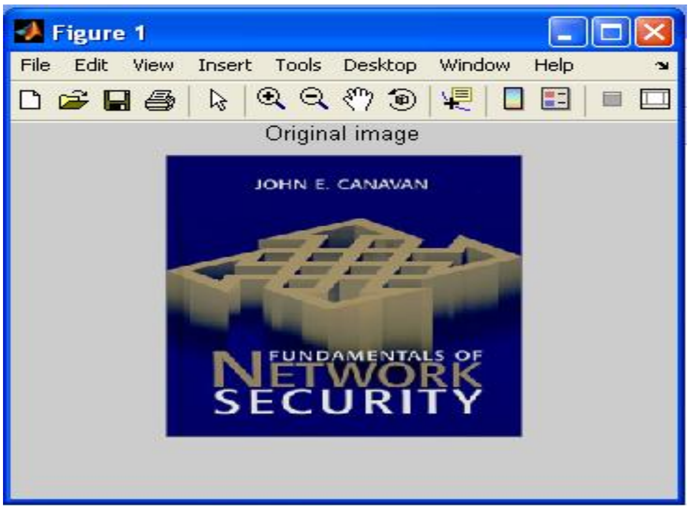
Figure a

Figure b

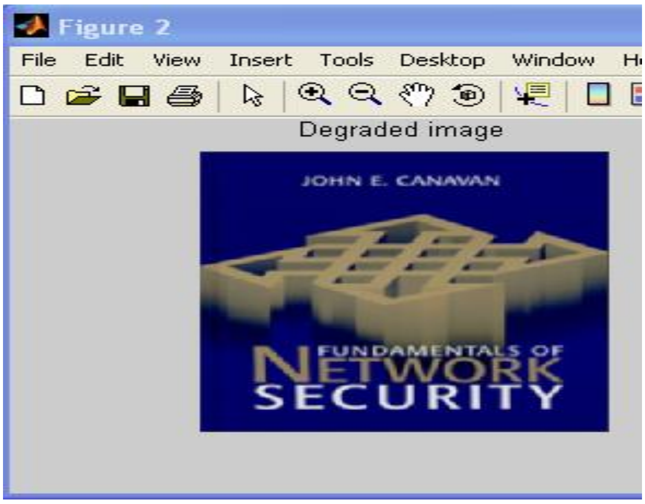
- ➢ Copy the files into the current directory of the MatLab and run the main source code file :



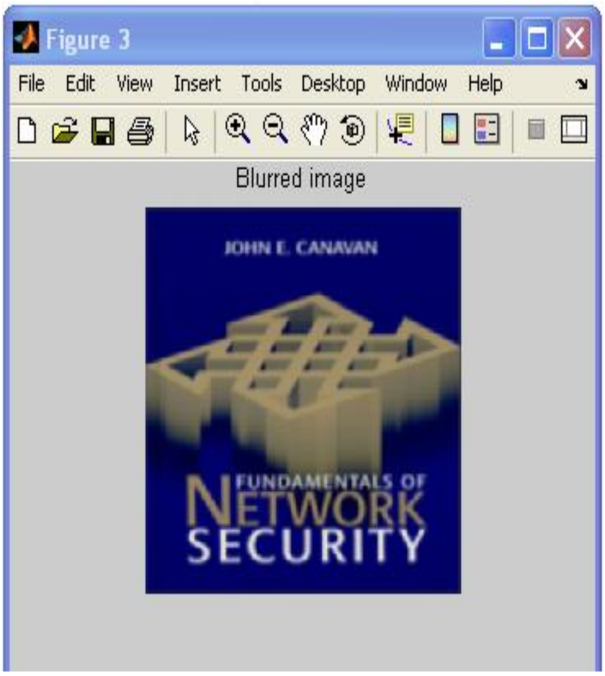
The following figure **a.1** represents the original Image



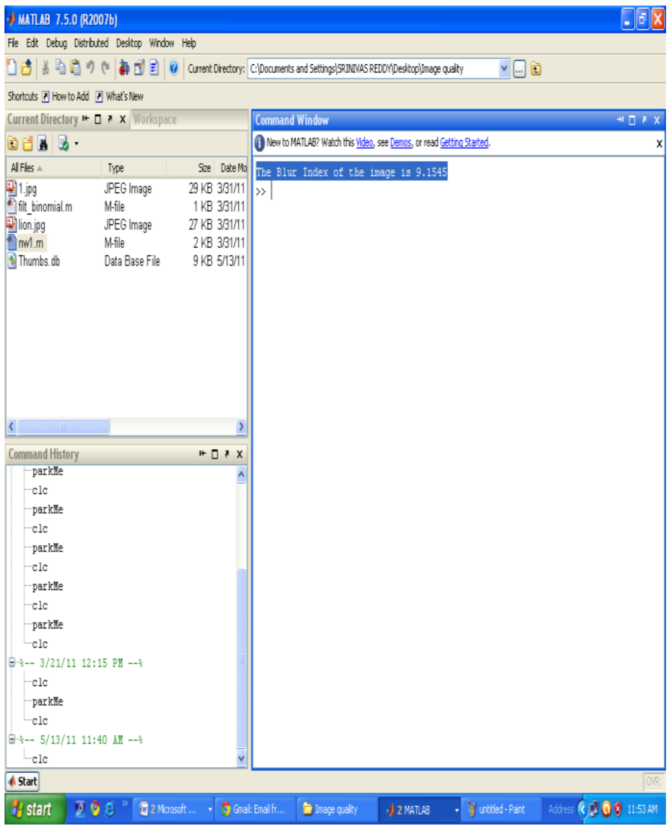
The following figure **a. 2** represents the Degraded Image



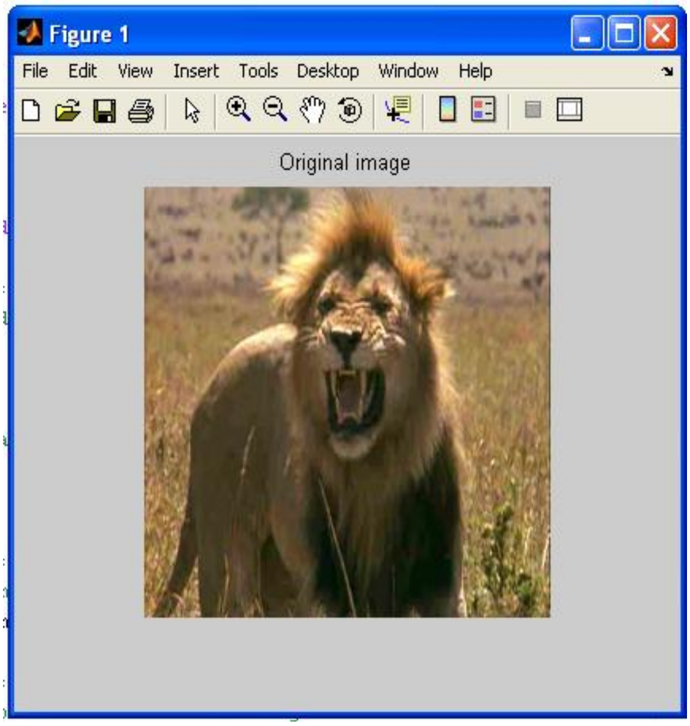
The following figure **a.3** represents the Blurred Image



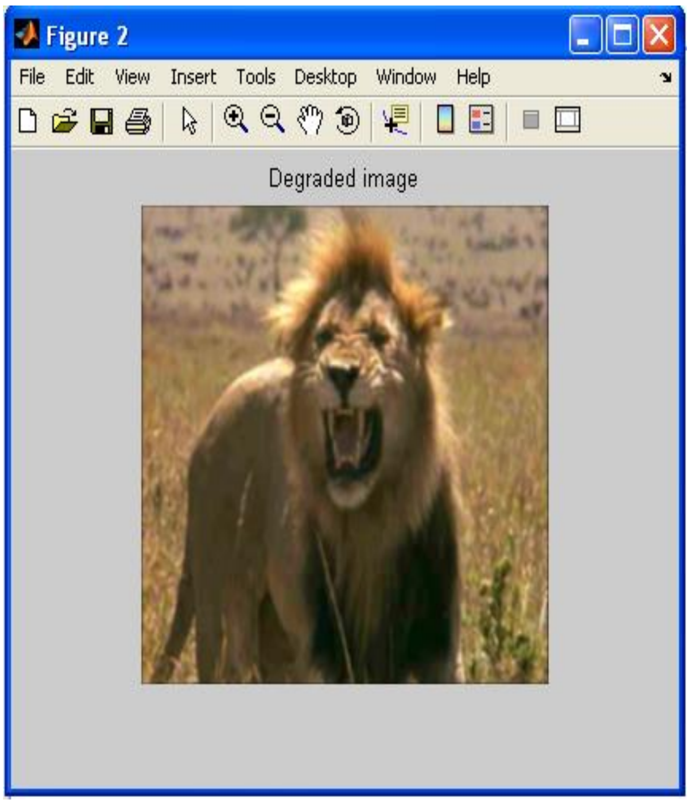
The blur image index for figure a is 9.1545



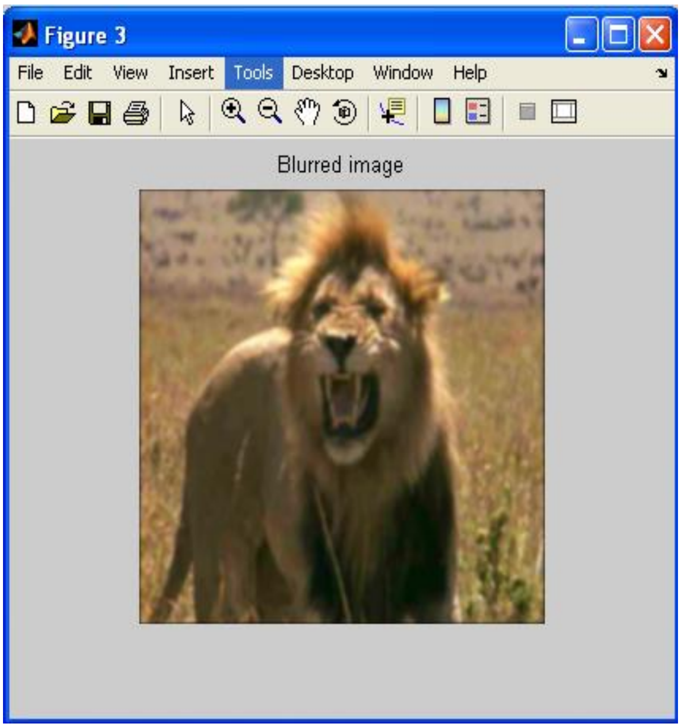
The following figure **b.1** represents the original



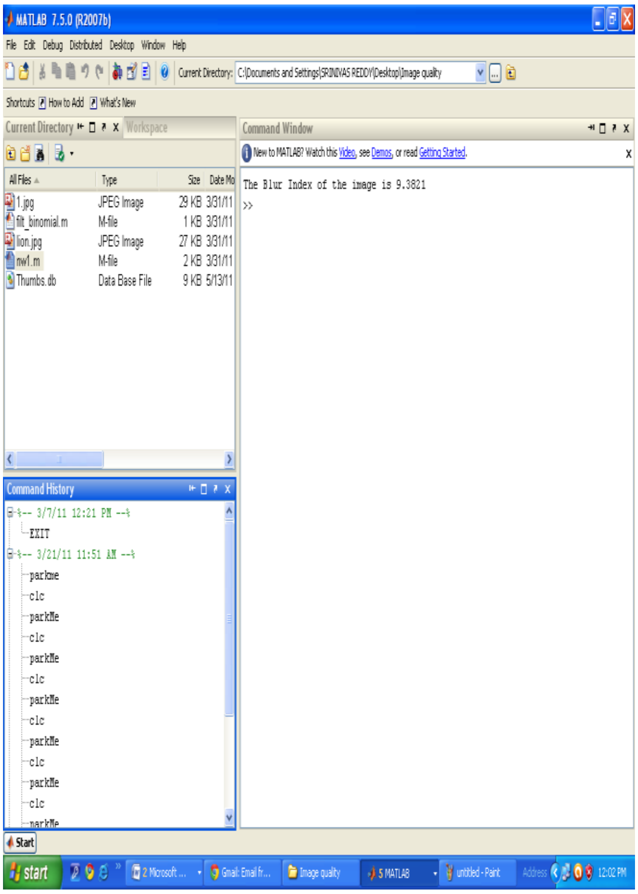
The following figure **b. 2** represents the Degraded Image



The following figure **b.3** represents the Blurred



The blur image index for *figure b.* is 9.3821



VI. APPLICATIONS OF MOTION BLUR

1) Photography
2) Computer animation

Photography

When a camera creates an image, that image does not represent a single instant of time. Because of technological constraints or artistic requirements, the image represents the scene over a period of time. As objects in a scene move, an image of that scene must represent an integration of all positions of those objects, as well as the camera's viewpoint, over the period of exposure determined by the shutter speed In such an image, any object moving with respect to the camera will look blurred or smeared along the direction of relative motion. This smearing may occur on an object that is moving or on a static background if the camera is moving. In a film or television image, this looks natural because the human eye behaves in much the same way.Because the effect is caused by the relative motion between the camera, and the objects and scene, motion blur may be avoided by panning the camera to track those moving objects. In this case, even with long exposure times, the objects will appear sharper, and the background more blurred.

Computer animation

Similarly, in real-time computer animation each frame shows a perfect instant in time (analogous to a camera with an infinitely fast shutter), with zero motion blur. This is why a video game with a frame rate of 25-30 frames per second will seem staggered, while natural motion filmed at the same frame rate appears rather more continuous. Many next generation video games feature motion blur, especially vehicle simulation games. In pre-rendered computer animation, such as CGI movies, realistic motion blur can be drawn because the renderer has more time to draw each frame.

VII. CONCLUSIONS & PERSPECTIVES

An efficient no-reference blur quality index is proposed. The method is not based on edge detection as most existing methods. Instead, we use a basic radial analysis in the frequency domain to measure the impact of blur added to the original image. The obtained results in terms of correlation with the subjective tests prove the efficiency of the proposed method. The efficiency of the proposed method could be improved by taking into account some HVS properties as contrast sensibility function.

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