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(RESEARCH ARTICLE)

Performance evaluation of digital filters for Yorùbá optical character recognition systems

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Abstract

Computer vision systems largely depend on the quality of output of the image processing modules to perform their operations for a desired accurate result. The process of image acquisition and transmission usually results in image degradation. This endangers the efficiency of computer vision systems. This paper presents the causes of image degradation and the restoration techniques to enhance the output of computer vision systems. At different filter kernel sizes, median filters have better performance in image restoration as shown in the SNR, PSNR, and MSE results obtained. Averaging filters result in a blurring effect on the image. Wiener filters perform better for speckle and Gaussian noise. For impulse (salt and pepper) noise, median filters have the best performance.

Keywords: Convolution; Degradation; Filter kernel; Mean squared error (MSE); Peak signal to noise ratio (PSNR); Restoration

1. Introduction

Digital image degradation is a result of the image being corrupted during acquisition or transmission within the imaging system. The degradation includes additive noise, blurring, and distortion due to the relative motion of the camera to the object being observed. Noise is the unwanted stochastic (random) fluctuation in the pixel intensities of a digital image. Restoration algorithms attempt to recover an image that has been corrupted or degraded with noise using foreknowledge of the degradation function. Therefore, the restoration process models the degradation function and applies the inverse process to recover the corrupted image as close as possible to the original image [1].

Quantum noise which results from electromagnetic radiation's distinct character and interaction with matter, in CCD devices, thermal noise, sampling noise owing to aliasing, and electronic noise in detectors and amplifiers are all sources of noise in digital imaging systems [2].

Some sources of visual noise in digital images include:

- Variation in surface materials
- Illumination and contrast imbalance
- Error generated during the Analog-digital conversion
- Ageing, may result in 1 and 2.
- For motion images electrical and electromechanical may be inclusive

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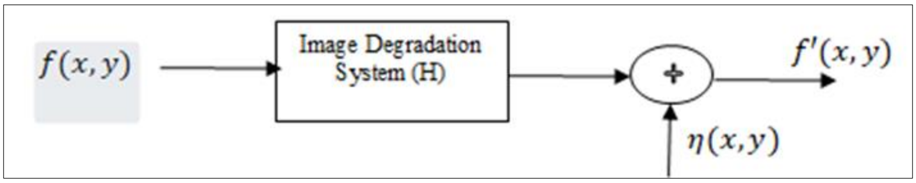
- Atmospheric turbulence [3]

The major effect of noise on computer vision applications (image processing and pattern classification /recognition) is that it leads to false positive or false rejection.

False positive and false rejection are as a result of mis-classification in computer vision systems or recognition systems. False positive is when an object in question is accepted for what it is not, i.e. the system says 'YES' when actually the answer should be 'NO'. The opposite is true for false rejection or false negative'. This has different terminology in applications or systems, they are called Type I and Type II errors in cyber security systems. The false rejection rate (FRR) and false acceptance error (FAE) are two forms of errors that are used to evaluate some recognition systems. Therefore, noise must be reduced to its possible minimum to achieve the best of the desired result in recognition.

In the spatial domain, the point spread function (PSF) and modulation transfer function (MTF) remove or mitigate these degradations [4].

Digital image degradation Model



[5]

Figure 1 Image Degradation Model

Figure1 shows the image degradation process and the addition of noise to an image signal. The degradation function with the addition of noise is made to operate on the image [6].

The mathematical model of the degradation process is given as:

$$f'(x,y) = H[f(x,y)] + \eta(x,y) \tag{1}$$

Where $f(x,y)$ the original or undegraded image, $f'(x,y)$ is the corrupted image and $\eta(x,y)$ is the additive noise.

H the degradation function is given as

$$H = h(x,y) \tag{2}$$

When H is set to convolve with the digital image in the spatial domain, the equation becomes

$$f'(x,y) = h(x,y) * f(x,y) + \eta(x,y) \tag{3}$$

The model equation in the frequency domain is as follows:

$$F'(u,v) = H(u,v)F(u,v) + N(u,v) \tag{4}$$

Convolution is an operation on two 2-dimensional functions which produces a third a function $f'(x,y)$, this can be interpreted as a modified (degraded) version of f.

The probability density function (PDF) dependends on the noise's mean and variance, PDF characterizes and describes noise in the spatial domain.

Noises in the spatial domain includes:

1.1. Gaussian Noise

Gaussian noise is generated mostly in amplifiers and detectors. It is, therefore, called electronic noise [2], Gaussian noise is called normal or white noise, the probability density function (PDF) of Gaussian noise is given as

$$P(z) = \frac{1}{\sqrt{2\pi\sigma}} exp(-z-\mu)^2/2\sigma^2 \qquad (5)$$

Where,

z the grayscale image

μ the mean of the noise

σ the variance or standard deviation of the noise pixel

Gaussian noise pixel values are approximately 70% in the range

$$(\mu - \sigma),(\mu + \sigma) \quad] \qquad (6)$$

and about 95% in the range

$$[(\mu - 2\sigma),(\mu + 2\sigma)] \qquad (7)$$

1.2. Impulse Noise

The PDF for impulse noise, often known as "Salt and Pepper" noise, is as follows:

$$P(z) = \begin{cases} P_a; & \text{for } z = a \\ p_b; & \text{for } z = b \\ 0; & \text{otherwise} \end{cases} \qquad (8)$$

Salt and pepper noise is created by data transmission faults [7], in which degraded pixels are set to a maximum value or zero, thereby resulting in the image salt and pepper appearance. The effect of salt and pepper noise is always quantified by the density of the affected image since the unaffected pixels remained unchanged [6]. Impulse noise is generally digitized as extreme pure black and white values in the image.

2. Rayleigh Noise

Rayleigh noise's PDF is as follows:

$$P(z) = \begin{cases} \frac{2}{b}(z-a)e^{-(z-a)^2} & \text{for } z \geq a \\ 0; & \text{otherwise} \end{cases} \qquad (9)$$

Its mean is given as

$$\mu = a + \sqrt{\frac{\pi b}{4}} \qquad (10)$$

and variance (Standard Deviation given as

$$\sigma = \frac{b(4-\pi)}{4} \qquad (11)$$

Other types of digital image noise are

Exponential Noise’s PDF is given as

$$P(z) = \begin{cases} ae^{-az} & \text{for } z \geq 0 \\ 0\ ; & \text{otherwise} \end{cases} \qquad (12)$$

Uniform Noise's PDF is given as

$$P(z) = \begin{cases} \frac{1}{b-a} & \text{for a} \leq z \leq b \\ 0\ ; & \text{otherwise} \end{cases} \qquad (13)$$

2.1. Gamma (Erlang) Noise's PDF

$$P(z) = \begin{cases} \dfrac{a^b z^{b-1}}{(b-1)!} & \text{for } z \geq 0 \\ 0 & \text{otherwise} \end{cases} \qquad (14)$$

2.2. Digital Image Restoration

A digital image may be corrupted or degraded by any of the aforementioned factor, restoration strategies focus on modelling the deterioration process and using the inverse of the degradation process to restore the original image. [1][8].

The degradation and restoration will be obtained using the model below

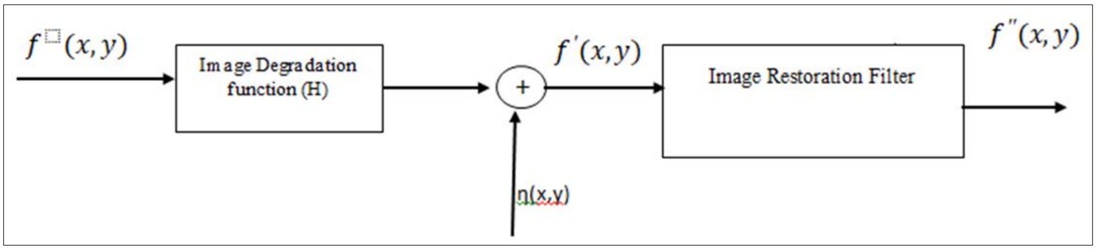


Figure 2 Degradation and Restoration Model [6]

The degradation process is given as

$$f^{'}(x,y) = H[f(x,y)] + \eta(x,y) \qquad (15)$$

The restoration process is given as

$$f''(x.y) = h(x,y) * f'(x,y) \qquad (16)$$

The basic objective of the restoration process is to obtain $f^{''}(x,y)$ as an estimate of $f'(x,y)$

Such that $f^{''}(x,y)$ is as close as possible to the original image. This is dependent on the prior knowledge of H and $\eta(x,y)$ which is degradation function and the additive noise. Digital image restoration has a great effect on the success of image classification and recognition in computer vision applications. Digital image restoration depends largely on the ability to simulate the behaviour and effect of each type of noise on the digital image[9].

In this research work, we concentrated on degradation and restoration in the spatial domain.

Gaussian, impulse and multiplicative (Speckle) noises were used to degrade several digital images. Several Gaussian noise mean and variance (standard deviation) values were explored.

Several levels of noise density were used for impulse noise and several values of variance were used for speckle noise because speckle is uniformly distributed noise with zero mean.

2.3. Image Restoration Algorithm

- Step 1: Start
- Step 2: Read in the degraded image
- Step 3: Detect image colour map
- Step 4: Set the image pixel intensity threshold
- Step 5: Extract image edge pixel intensity; set region of interest ROI
- Step 6: Estimate image pixels priority to be repaired
- Step 7: Sparse reconstruction of block ROI
- Step 8: Update image ROI pixels confidence
- Step 9: Is the repair complete;
  - If
    - YES
    - Map reconstructed pixel to original image
    - Output
  - Else
  - Go to step 5
- Step 10: End

3. Results and discussion

To examine and quantify the quality of an image for comparisons, numerous image quality measuring approaches are utilized [7]. Signal to noise ratio (SNR), peak signal to noise ratio (PSNR), mean squared error (MSE)[10], universal image quality index (UIQI), structural similarity index method (SSIM), human vision system (HVS), featured similarity index technique (FSIM) [8] are the most efficient and widely used metrics.. Three of these strategies were chosen for this project.

3.1. Signal to Noise Ratio

SNR measures the sensitivity of imaging, it signifies the image strength relative to the background noise [10].

The signal-to-noise ratio (SNR) of an image is expressed as

$$SNR = 10 * log_{10}\frac{\mu}{\sigma} \qquad [11] \qquad (17)$$

μ - The mean value of the input image pixels
σ - The variance of the image pixel and the background pixels
SNR - Signal to noise ratio

3.2. Peak Signal to Noise Ratio

PSNR is used to determine the degradation in the embedded image with respect to the host image[10]. PSNR is calculated using the ratio of the maximum possible signal power to the power of the distorting noise which affects the quality of its representation. This ratio between the two images is computed in decibel form. PSNR is given as:

$$PSNR = 10log_{10}\frac{L^2}{MSE} \qquad (18)$$

“L = is the peak signal value (image)”

“MSE = is the mean squared error”

3.3. Mean Square Error

MSE is the average squared difference between a reference image and a degraded image [11]. MSE is evaluated as;

$$MSE = \frac{1}{xy}\left[\sum_{i=1}^{x}\sum_{i=1}^{y}(c(i,j) - e(i,j))^2\right] \qquad (19)$$

It was observed that the level of degradation differs and therefore, there are differences in SNR of the degraded images.

The restoration was carried out using a Linear Averaging filter and non-linear filters (Median filter) with different sizes of the convolution kernel. Linear filters were observed to be more effective in removing Gaussian noise from the images leaving behind a blurring effect at the edges of the image. This showed its manifestation in figure (3) the original, corrupted and filtered image using different filters. Also in figure (4) in the pixel intensity distribution histogram of the original, corrupted and restored image. The blurring effect is a result of padding at the edges. Non-linear (median) filter showed more effectiveness in removing the salt and pepper noise. This is evident in the SNR of the output images as shown in table 1.

Table 1 Comparison of SNR of output image after restoration using Linear and Non-linear filter

μ	σ1	SNR 1	σ2	SNR2	σ3	SNR3	σ4	SNR4	σ5	SNR5	σ6	SNR6
255	19.048	11.2668	19.941	11.067	31.168	9.128	39.670	8.080	5.013	17.063	11.325	24.065
208.714	35.880	7.64688	38.324	7.360	48.919	6.300	59.845	5.425	55.847	5.725	69.735	4.783
210.685	50.340	6,21714	54.644	5.860	46.211	6.588	49.839	6.260	52.98	5.995	68.296	4.892
214.957	47.343	6.57984	53.801	6.015	47.601	6.547	48.708	6.447	48.174	6.945	60.371	5.525
214.871	46.625	6.63555	50.740	6.268	46.145	6.680	48.141	6.496	46.716	6.627	54.382	5.967
212.314	44.979	6.73963	48.186	6.440	43.826	6.852	43.685	6.866	50.530	6.234	66.583	5.068
218.5	35.866	7.84766	39.308	7.449	35.624	7.877	38.644	7.557	43.493	7.011	44.282	6.932
209.171	28.032	8.72843	8.728	8.218	27.476	8.815	32.294	8.113	40.630	7.116	59.020	5.495

μ **-** Mean pixel values of a greyscale image
σ1 Variance of pixels of linear filtered Gaussian degraded image
σ2 Variance of pixels of linear filtered salt & Pepper degraded image
σ3 Variance of pixels of non-linear filtered Gaussian degraded image
σ4 Variance of pixels of non-linear filtered salt & Pepper degraded image
σ5 Variance of pixels of Gaussian noise degraded image

Table 2 Comparison of PSNR, SNR and MSE Filtered Noises

Impulse Noise				
	Degraded Grayscale Image	**Mean Filter**	**"Wiener Filter"**	**Median Filter**
PSNR	17.8767	19.8906	23.0653	23.9845
SNR	14.8750	16.8888	20.0635	29.9823
MSE	59.1825	52.1317	55.6390	58.0380
Speckle Noise				
PSNR	24.3969	19.8518	27.8394	22.2790
SNR	21.3591	16.8500	24.0374	19.9452
MSE	59.1825	50.3066	52.8211	55.4624
Gaussian Noise				
PSNR	20.8069	19.8652	26.3729	22.8069
SNR	17.8051	16.8654	23.3711	19.8041
MSE	59.1825	50.8985	53.2210	55.9818

Figure 3 Processed output image using different filters

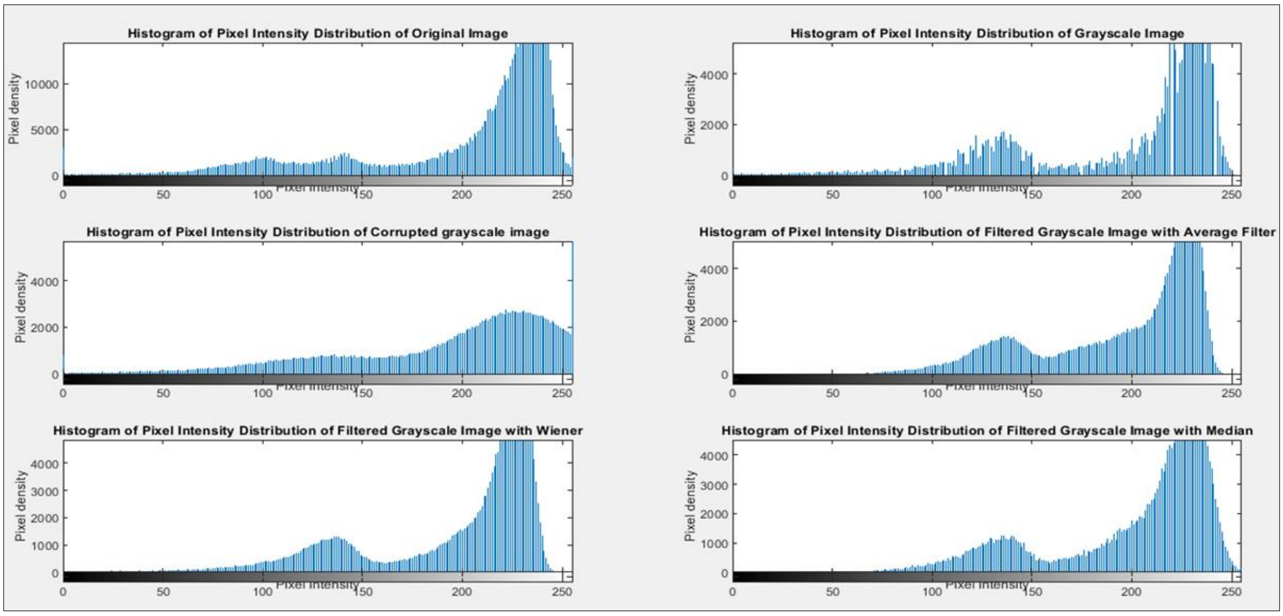


Figure 4 The histogram comparison of original, degraded and restored image with different filters

4. Conclusion

At different filter kernel sizes, Wiener filters have better performance in restoration than all other filters for all sample noised images used under investigation. At higher a filter kernel, averaging filter results in a blurrier image. Also, the Wiener filter. While median filter performs better for impulse (Salt and pepper) noise.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest.

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