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Image Enhancement Methods: A Review

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Review Article

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Abstract

Image processing is faced with a number of challenges ranging from unequal resolutions, format variations, non uniform illuminations, distortions and noise. It is also affected by orientation and contrast differences. In view of these challenges, most digital image processing applications or devices employ enhancement procedure prior to the use of the captured image for intended purposes. This paper reports on the review of some of the existing digital image enhancement methods with emphasis on methodologies, strengths, limitations and application areas. The specific application of some of these methods by different authors is also presented.

Keywords: Image Processing, algorithms, noise and artifacts, image digitization, image enhancement.

1 Introduction

An image is a representation or general impression of an object. It is also an artifact which depicts or records visual representation in any two-dimensional picture with similar appearance to living object or any physical structure such as map, graph, chart or abstract painting. An image may be rendered manually by drawing, painting or carving while automatic rendering of image includes printing and computer graphic. During the process of capturing, storage, modification and viewing, an image must be converted to a set of numbers in a process called digitization or scanning. Once an image has been digitized, computer can be used to archive, examine, alter, display, transmit, or print it. Commonly known images include gray-scale (black and white), colour, binary or bi-level and index colour (multi spectral) [1-2]. The process of the enrolment or capturing of images faces a number of challenges ranging from unequal resolutions, format variations, non uniform illuminations, distortions and noise. Other external issues are variations in orientation and contrast [3-11]. In most cases, these challenges prompt the implementation of enhancement algorithms prior to usage. A noisy image and its enhanced version are shown in Fig. 1. Most image enhancement algorithms tend to be simple, qualitative and improvised while their performance levels vary from application to application.

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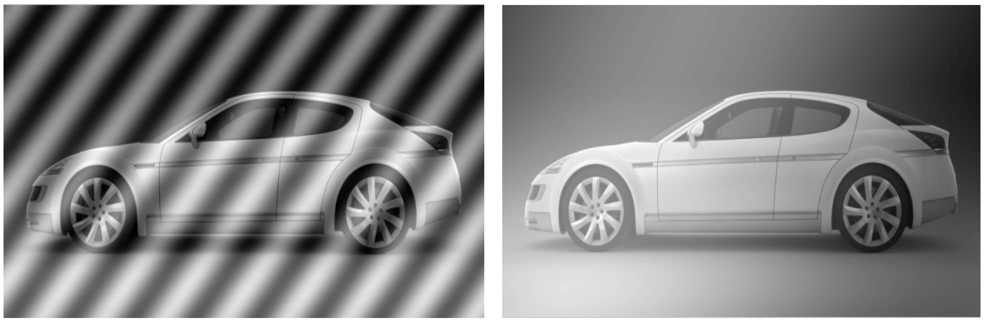

(a) (b)

Fig. 1. (a) original and noisy image, (b) Enhanced image

Section 2 of this paper discusses some recently formulated image enhancement techniques while the review of some recent research works on digital image enhancement is presented in Section 3. Sections 4 and 5 focus on some notable application areas of image enhancement and the conclusion drawn respectively.

2 Image Enhancement Techniques

Some of the existing image enhancement techniques are discussed in the following sub-sections [12-19]:

2.1 Interpolation

Interpolation is a primary technique for image scaling in geosciences studies, astronomy, facial reconstruction, multiple-description coding, resolution enhancement and geographical information systems. It involves the generation of a new resolution-enhanced and sharper version of an image. Existing interpolation techniques include adaptive Sub-Pixel [20], high-frequency sub-band by discrete wavelet [21], bi-linear/bi-cubic [20], Vector Quantisation [22] and dual tree-complex wavelet [23]. In most cases, the image is enlarged to a scale factor derived from the mean, median or maxima of its neighbouring pixels. As shown in Fig. 2, an image is expanded to size (2n-1) x (2m-1) and the defined pixels are marked with 'X' while the undefined pixels are filled by taking the average values of the neighbouring pixels. Primarily, interpolation algorithms map pixels from successive low-resolution frames onto a single high resolution frame with the sub-pixel shift information. The resulting non-uniformly filled virtual frames are also interpolated to an enlarged frame with evenly-spaced pixels. Each pair of neighbouring frames generates magnified and enhanced image frame [24].

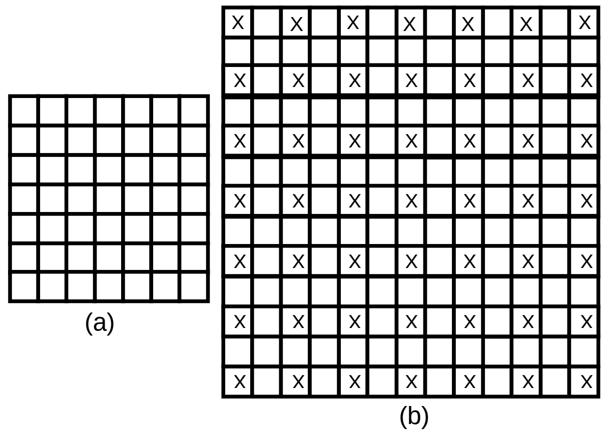

Fig. 2. (a) Original image of size m x n, (b) Expanded image of size 2m-1 x 2n-1

The zooming of an image is an important task in many applications, including the World Wide Web (WWW), digital videos (DVDs) and scientific imaging [25]. When zooming, pixels are inserted into the image in order to increase its size, and the interpolation of the new pixels from the surrounding and original pixels is performed. Similar problem requiring interpolation by weighted medians is interlacing progressive video conversion for television systems [26]. Interpolation promotes edge preservation and a less “blocky” look to edges.

2.2 Contrast Stretching (CS)

Contrast refers to the difference between the intensity of two adjacent pixels in an image. Low-contrast images emerged from non-uniform lighting conditions, non-linearity or small dynamic range of the imaging sensor. Contrast stretching focuses on improving the contrast in an image by `stretching' its range of intensity values to span a desired or permissible range. It equalizes the contrast throughout the image via simultaneous adjustment of each gray value at the darkest and lightest portions, thereby promoting the visualization of the details and structure of the very light or dark regions. It differs from the other algorithms in that it only applies a linear scaling function to the image pixel values resulting in a less harsh result. Prior to stretching, it is necessary to specify the upper and lower pixel value limits over which the image is to be normalized. Often, these limits are assumed to be the allowable minimum and maximum pixel values for the image type. For example, in 8-bit level images, the lower and upper limits are set to 0 and 255 respectively. An image contrast stretching transformation may be obtained from [27-28]:

$$C(i,j,k) = \begin{cases} \delta(f(i,j,k) \; for \; 0 \leq f(i,j,k) \leq x \\ \rho(f(i,j,k) - x) + C(i,j,k) * x \; for \; x < f(i,j,k) \leq y \\ \varphi(f(i,j,k) - y) + C(i,j,k) * \; y \; for \; y < f(i,j,k) \leq W \end{cases} \tag{1}$$

Where * is a multiplication operator, $x = W/3$, y= $2W/3$, $\mathrm{C(i,j,k)} = \frac{W}{3} * \; x = \delta * x$, $\mathrm{C(i,j,k)} = \frac{W}{3} * \; y = \rho(y - x) + C(i,j,k) * x$, for a dark region, $\delta > 1$ while $\rho > 1$ at mid region. W is the number of levels.

In recent years, digital video cameras have been employed not only for video recording, but also in a variety of image-based technical applications such as visual tracking, surveillance and amplifier. Although, the trend of effort at capturing is diminishing, the images taken from a camera usually suffer from noises, low dynamic range (LDR), poor contrast, colour distortion and so on. As a result, contrast stretching is often used to eliminate or reduce these problems for improved visual quality. Though contrast stretching has proved very suitable for applications in GIS and medical images, it is currently seeking improvement in the area of computational complexity for real-time video applications [29].

2.3 Histogram Equalization (HE)

HE is a point operation that maps an input image (with unequal level intensities) to its output image (with equal level intensities). The ultimate objective is to standardize the intensities in the output image to a level that is close to the form presented in Fig. 3(b) as much as possible.

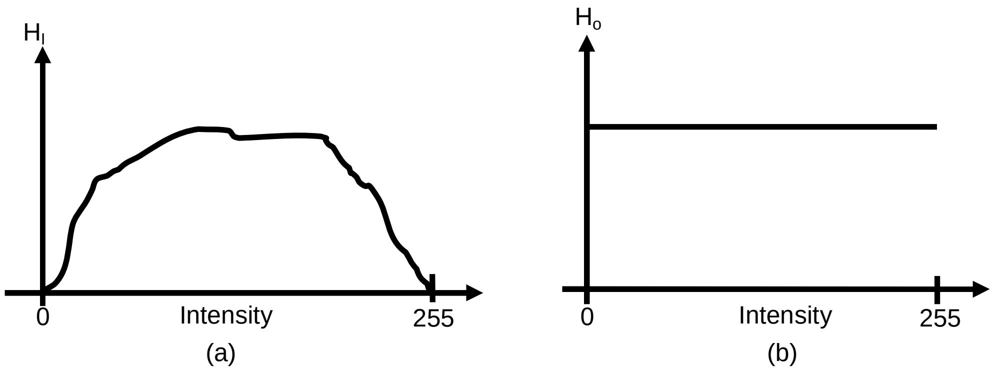

Fig. 3. (a) Intensity curve of input image (b) Intensity curve of output image

Due to its computational simplicity and comparatively better performance, HE is mostly used in computer vision to obtain improved colour images [30-33] as well as higher brightness of gray scale medical images [32, 34-35]. Generally, HE preserves the image details such that both global and local contrasts are enhanced with minimum distortion in the image appearance. The histograms of a noisy image (Fig. 1(a)) and its enhanced version obtained through HE (Fig. 1(b)) are presented in Fig. 4(a) and 4(b) respectively. Fig. 4(b) shows adjustment of the intensity values such that there is improved distribution of intensity between the dark and light regions. In most HE, consideration is given to discrete variable V at level L with the distribution function D^V (histogram). $D^V_{L_r}$ is also considered as the occurrence of L_r level where $0 \leq L_r \leq L-1$. If C^V and $C^V_{L_r}$ are the cumulative density function of V and L_r respectively then $C^V_{L_r}$ is derived from [36]:

$$C^V_{L_r} = \sum_{L_{r=0}}^{L_r} D^V_{L_r} \tag{2}$$

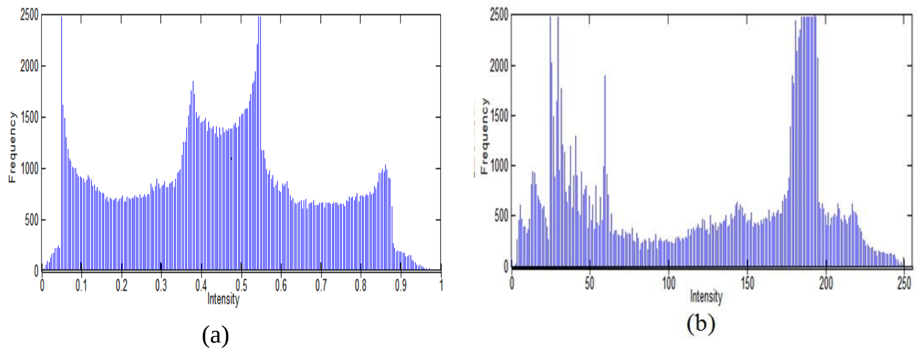

Fig. 4. (a) Histogram of the noising image shown in Fig. 1(a); (b) Histogram of the noising image shown in Fig. 1(b)

Based on Equation (2), HE sets the uniform distribution D^V over the entire image and produces an aggregate (cumulative) density function that monotonically increases linearly. Given that O and E are the original and equalized images respectively, then the values L_o, L_E = 0, 1, 2, . . . ,L – 1 are set for histogram D^V and cumulative density function C^V. If D^E is the desired uniform histogram, then each frame of an image of height, A and width, B has the same density (amount of pixels) defined by:

$$D_{L_E}^E = \frac{1}{L}(A \times B) \quad (3)$$

The cumulative density function C^E is then obtained from:

$$C_{L_E}^E = \sum_{L_{E=0}}^{L_E} D_{L_E}^E = \frac{L_E + 1}{L}(A \times B) \quad (4)$$

If L_E turned out to be the smallest value of C^E for which $C_{L_E}^E - C_{L_O}^O \geq 0$, then L_E is taken as the output equalized level which corresponds to the input level L_O. This implies that the output level L_E can be computed as the transformation function $F^O|L_O|$ given by:

$$L_E = F^O|L_O| = \leftrightarrow \left(\frac{L * D_{L_O-1}^O}{(A \times B)}\right) \quad (5)$$

↔(•) represent the function that returns the nearest integer. This technique is easily extended for colour image enhancement by separate application of the equalization process to each of the RGB channels.

The histogram equalization algorithm has proved to be a very reliable way for the integration of colour and brightness information extracted from salient local features of colour images. It also does well in the attenuation of noise, blurriness and poor contrast. Regrettably, it experiences failure with inappropriate parameter selections, requires square complexity of time and space and susceptible to failure in unrecoverable corrupted image regions [37-38].

2.4 Dynamic Range Compression

Dynamic range compression is used to represent a large input dynamic range by its relatively small output equivalent. It is expressed as the difference or ratio between the brightest intensity and the darkest intensity of an image or scene which can be compressed via the logarithmic transformation when it is very large [29]. It is generally believed that human vision system involves a number of complex activities and various adaptive mechanisms that positioned it to capture a scene with large dynamic range through various adaptive mechanisms. This is not the case in images produced by video cameras which are without real-time enhancement processing and cannot produce good visual contrast at all ranges of signal levels. Consequent to this, local contrast often suffers at regions with low or high signal averages. Dynamic range compression is therefore used to improve local contrast at all regional signal average levels within the 8-bit dynamic range of most video cameras so that image features and details are clearly visible at the dark and light zones. When the dynamic range of an image data is very large, it is compressed by using a typical logarithmic transformation as follows:

$$\mathrm{C(i,j,k)} = \mathrm{k} * \log_{10}(1 + |\mathrm{f(i,j,k)}| \tag{6}$$

$$k = \frac{W}{log_{10}(1+W)} \tag{7}$$

This method adjusts the intensity for effective compression of the dynamic range of the image towards ensuring effective mapping of the high to the small dynamic range scenes. This helps to avoid sundry artifacts and loss of local contrast. Dynamic range compression, like contrast stretching and histogram equalization, is also noted for satisfactory removal of noise, blurriness and poor contrast in medical (digital X-ray, digital mammongraphy, CT Scans and MRI), surveillance and satellite images. Its suitability for other image applications such as biometrics is still in contention [39].

2.5 Partial Differential Equation (PDE) Method

Various PDE methods have been developed over the years for image restoration, filtering, segmentation and object tracking. With PDE, invariances are offered with respect to classical techniques alongside re-interpretation of traditional techniques such as convolution, filtering and morphological operations of dilation/erosion under a novel unifying framework [40]. It has greatly improved mathematical modelling, connection with physical phenomena and approximation to the geometry of the problem as well as performing shape recognition, structure-preserving filtering and object segmentation in a stronger and more intuitive framework. The use of average, median, Gaussian and other form of filters helps reduce noise at the cost of smoothing the image and hence softening the edges. PDE-based image enhancement methods, which are premised on the assumption that the intensity of illumination on edges varies like geometric heat flow are used to solve this problem. For an image I, a typical second order PDE based on heat diffusion equation is defined as follows [10,41]:

$$\frac{\partial I}{\partial t}(i,j,t) = \rho\big(\mathrm{c}(i,j,t)\nabla I(i,j,t)\big) \tag{8}$$

$$\mathrm{I}(i,j,0) = I_0(i,j) \tag{9}$$

∇ is the gradient operator, *c(i, j, t)* is the diffusion factor, and ρ is the divergence operator. Two different equations for the diffusion factor are as follow:

$$\mathrm{c}(i,j,t) = \frac{\gamma^{-2}}{\gamma^2 + |\nabla I|^2} \tag{10}$$

$$\mathrm{c}(i,j,t) = exp\left(-\frac{|\nabla I|^2}{2\gamma^2}\right) \tag{11}$$

γ is a constant for controlling the diffusion factor *c* which changes at different points in the image and has small value for points (mostly around the edges) with large gradient. The fourth order PDE uses the L^2 – curvature gradient flow method as follows:

$$\frac{\partial I}{\partial t} = -\nabla^2[\mathrm{c}(\nabla^2\mathrm{I})\nabla^2\mathrm{I}] \tag{12}$$

∇^2 represents the Laplacian of the image and Equation (12) is associated with the following energy functional for a given image support τ:

$$E(I) = \int_\tau f(|\nabla^2\mathrm{I}|)\,\partial x\,\partial y \tag{13}$$

The existing PDEs-based image enhancement techniques are very good for image filtering and restoration in computer vision and other related applications. They are also suitable for solving image quality problems arising from shape evolution, morphology, optical flow estimation and shading which are all governed by (partial) differential equations [42]. Current issues against this method include lack of discretization schemes for the numerical analysis of continuous PDE models, performance degradation when subjected to images with significant noise energy [10,43] as well as demand for high mathematical skills and good insight to the problems.

2.6 Alpha Rooting

Alpha rooting is a combined frequency and spatial domain enhancement technique, wherein the frequency domain technique complements the spatial domain technique in order to optimize the advantages and minimize the limitations of both techniques. It is usually used to accentuate the high frequency content of the image by using power law and log transforms to map a narrow range of input gray levels to a wider output range thereby improving contrast and at the same time retaining the subtle information and perceivable details. It is also used to augment the high frequency content in the image by applying Fourier, discrete cosine or Hartley transforms. The visual result presents a higher emphasis on detail such as edges and fine distinguishing features.

The application of orthogonal transform makes the high frequency coefficients of an image to have smaller magnitudes than low frequency coefficients. By raising the magnitude of an image to some value, δ, where $0 < \delta < 1$, the higher valued lower frequency components are reduced more in proportion to the lower valued higher frequency components. This proportional reduction of magnitudes leads to emphasizes on high frequency content of an image. Alpha rooting has long been used for enhancing high contrast edge information and sharp features in images where the inverse orthogonal transform is firstly applied to get the output image followed by the computation of the magnitude and phase difference. A typical phase difference formula is presented as follows [44];

$$\emptyset(\mathrm{e,f}) = |\emptyset(\mathrm{e,f})|\mathrm{e}^{\mathrm{m}\varphi(\mathrm{e,f})} \tag{14}$$

$\emptyset(\mathrm{e,f})$ represents the orthogonal transform of the image, $|\emptyset(\mathrm{e,f})|$ is the magnitude of the transform and $\varphi(\mathrm{e,f})$ is the phase angle of the transform. Alpha rooting is applied as follows:

$$|\emptyset(\mathrm{e,f})|^{\partial}, \quad 0 < \partial < 1 \tag{15}$$

The phase angle and the alpha rooted magnitude are combined by using the formula:

$$\widehat{\emptyset}(\mathrm{e,f}) = |\emptyset(\mathrm{e,f})|^{\partial}\mathrm{e}^{\mathrm{m}\varphi(\mathrm{e,f})} \tag{16}$$

To return from frequency to spatial domain, inverse orthogonal transform is applied and the obtained image is subjected to logarithm transform as follows:

$$\mathrm{f} = \mathrm{k} * \log(1 + \mathrm{g}) \tag{17}$$

g and f are the gray level of the input and output pixels respectively and k is the scaling constant. Power law transformation, which produces the enhanced image is then applied by using:

$$\mathrm{p} = \mathrm{s} * \mathrm{g}^{\vartheta} \tag{18}$$

p is the output gray level, s is the scaling factor and ϑ is the power to which the input gray level is raised. Alpha rooting is simple in theory and implementation and is capable of eliminating the shortcomings of the conventional domain transform technique such as graying, tonal changes and artifacts in colour images. It is also used for improving images with low contrast and unbalanced distribution of gray levels [44].

2.7 Cellular Neural Networks (CNN)

Cellular neural network (CNN) is currently a very appropriate computing model for providing solution to numerous image processing problems. It is based on multi-valued neurons [45] and universal binary neurons [46] which both work with complex-valued weights and complex internal arithmetic. CNNs based on these complex-valued neurons can be combined with noise removal to implement image enhancement with high and medium frequencies amplifiers [36]. Cellular Neural networks are well known for their good performance in classification and function approximation. They have been used with success in medical image enhancement and analysis, particularly in the case of signal classification in support of diagnosis, filtering, compression and restoration [47]. It is also used in resonance image filtering, edge detection as well as character and object recognition. Due to the parallelism of its architecture, it can be applied to problems such as video signal processing where traditional methods cannot deliver fast throughput [48]. It can be defined over any dimension though it is much easier to visualize them in 1-D or 2-D. A 2-D CNN defined over a 3 x 3 lattice is illustrated in Fig. 5.

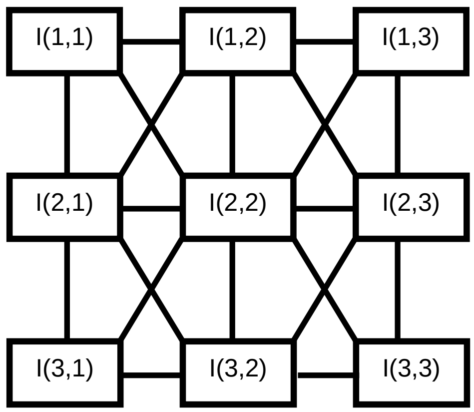

Fig. 5. 2-D CNN defined over a 3 x 3 square lattice

Shunting Inhibitory Cellular Neural Network (SICNN) is a biologically inspired system of image processing that provides contrast and edge enhancement and dynamic range compression. It is an efficient way to achieve lightness-colour constancy by enhancing the dark region and at the same time retaining the colours in the bright. With this approach, the neighbouring neurons exert mutual inhibitory interactions of the shunting. The dynamics, DR of this technique include range compression, colour constancy and rendition which are used for obtaining improved colour complementary metal-oxide semiconductor (CMOS) images. The dynamic range is used to compare the maximum signal level ∇V_m with the minimum rms noise level ΔV_m in an image and is obtained using integer constant k as follows [49]:

$$DR = k * log_{10} \frac{\nabla V_m}{\Delta V_m} \tag{19}$$

Generally, colour images are susceptible to colour constancy, which is the spectral distribution of the non-luminance changes. Hence, given that I_r is the normalized contrast or reflectance and I_t represents the total input, then:

$$I_i = I_r I_t \tag{20}$$

$$I_t = \sum_{k=1}^{n} I_k \tag{21}$$

Based on the approximation of the convolution term to the input current sources, the steady state solution is given by:

$$x_i = I_r \frac{I_t}{a + \sum_{k \neq i} I_k} \tag{22}$$

If the total activity is not perturbed by the activity of one cell, then:

$$\sum_{k \neq 1}^{n} I_k \approx \sum_{k=1}^{n} I_k = I_t \tag{23}$$

Hence, Equation (22) becomes:

$$x_i = I_r \frac{I_t}{a + I_t} \tag{24}$$

The total activity of the network is then computed from:

$$x_T = \sum_{i=1}^{n} I_r \frac{I_t}{a + I_t} = \frac{I_t}{a + I_t} \tag{25}$$

Equation (22) converges to 1 as mean intensity (background) increases resulting in brightness contrast.

CNN is good for compressing an image's dynamic range for better contrast and for enhancing the spatial edges as well as elimination of Fixed Pattern Noise (FPN). It however lacks the strength for handling automatic gain and exposure control or white balance which results in a wide gap in its handling of CMOS and Charge-Coupled Device (CCD) imaging quality [49].

2.8 Algebraic Reconstruction Method (ARM)

An image with high resolution (HR) has a high pixel density and therefore can offer more details that may be critical in various applications. Unfortunately and in several cases, the image resolution is limited by the aperture response and for many applications greater resolution is desired, leading to interest in image reconstruction and resolution enhancement algorithms. ARM makes a pixel responsible for the error it produced by using back projection and is greatly used in non-uniform interpolation, microwave remote sensors, optical sensors and gridded images [50-51]. Under normal circumstances, ARM provides improved resolution images by taking advantage of oversampling and the response characteristics of the aperture function to reconstruct the underlying surface function sampled by the sensor. Given that f represents the obtained solution, $d_{j,i}$ is the weight of the j-th pixel values when calculating the projection on the i-th ray and C_j represents the jth projection ray, the projection error, φ on that ray is derived from [8]:

$$\varphi = \sum_{j=1}^{m} \left(\sum_{i=1}^{n^2} d_{j,i} f_i \right) - C_j \tag{26}$$

$$A = \sum_{s=1}^{i^2} d_{j,s} \tag{27}$$

A is the aggregate of the weights on the jth ray and for the correction of the error, φ is back projected on the pixels hit by the ray based on the pixel weights. Thus, the new image f' will have the pixel values defined by:

$$f_1' = f_1 + d_{j,1}\frac{\varphi}{A}, \ . \ . \ ., \ f_{i^2}' = f_{i^2} + d_{j,i^2}\frac{\varphi}{A} \tag{28}$$

The method is repeated ray by ray, iteratively, until it terminates with the error on the given ray equals zero while it may rise on others.

Discrete Algebraic Reconstruction Technique (DART) has been developed for discrete image reconstruction by using image thresholding obtained by a continuous reconstruction method. This provides simpler discrete image reconstruction based on the fact that result from thresholding is often exclusively inaccurate along the object boundaries. Consequently, modification of the boundary pixels is iteratively carried out prior to an initial thresholding of a continuous result. Firstly, an initial continuous reconstruction is computed by using a variant of ART followed by thresholding of the actual image f_{act} through known discrete values which can be used to obtain f' of the image pixels. The set Z of non-boundary pixels is then computed paving way for the composition of a new image by taking the pixel value from f'if the pixel is located in Z and from f_{act} if otherwise. The ART iteration is performed on the non-boundary pixels of the composed image followed by smoothening of the boundary pixels. Finally, if the termination criterion is met, then a final thresholding is performed, otherwise, the operation is repeated. ARM is strong for the removal of unwanted effect of salt and pepper-like noise and reduction in the number of iterations and projections needed for an acceptable image reconstruction. It however experiences difficulty in finding the proper parameter values for the filter [8].

2.9 Directional Wavelet Transform (DWT)

DWT is an enhancement technique that is majorly used for retaining all the beneficial properties of wavelets and at the same time provides directional information decomposition in an image. Its notable examples include 2-D Gabor wavelets, the steerable pyramid, the directional filter bank, 2-D directional wavelets, complex wavelets, curvelets, ridgelets [52] and contourlets [53]. Its major strength is its ability to represent the singularities of the signal efficiently. For 2-D implementation, usually separable wavelets are used to represent vertical and horizontal edges [54]. DWT is mostly used in image processing applications, including feature extraction, enhancement, denoising, classification, and compression [55], Object-Based Scalable Video Coding [56], low bit-rate compression [57-58] as well as de-corrugation and removal of directional trends [59]. The directional wavelet transform (DWT) of a discrete image I(i, j) may be obtained from ([56,60]):

$$L_y(\beta, \delta, \vartheta, \sigma) = \sum_{i=0}^{R-1} \sum_{j=0}^{S-1} \frac{1}{\sqrt{\beta}} I(i,j)\, G(\sigma) L_\beta(\delta - i, \vartheta - j) \tag{29}$$

β is the scale parameter, $L_\beta(i,j)$ is the 2-D wavelet kernel and R and S represent the kernel's size. $G(\sigma)$ rotates the kernel counter clockwise by an angle σ. L_β is obtained from:

$$L_\beta(i,j) = \Delta_\beta(j), \qquad i \in [0, R-1] \tag{30}$$

The directional filter algorithm is defined by using 1-D Mexican Hat function given by:

$$\Delta(t) = \frac{2}{\pi^{0.25}\sqrt{3\gamma}}\left(\frac{t^2}{\gamma^2} - 1\right)e^{\left(\frac{-t^2}{2\gamma^2}\right)} \tag{31}$$

A typical Mexican Hat wavelet is shown in Fig. 6. The wavelet is derived without scaling from a function that is proportional to the second derivative of the Gaussian probability density function.

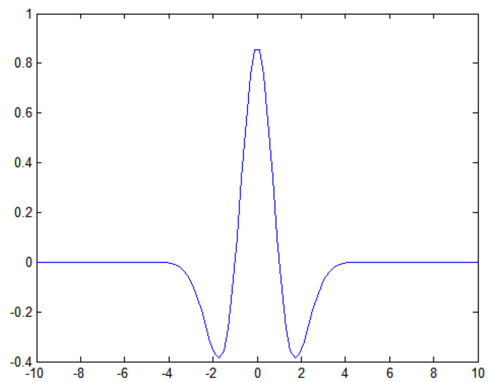

Fig. 6. Mexican Hat Wavelet

The strength of Directional Wavelength Transform (DWT) lies in its robustness and accuracy with effective enhancement of regions in the neighbourhood of most significant singularities of an image. Its weak points remain its high directional information cost and computational complexities [56,60].

2.10 Spatially Adaptive Iterative Filtering

The use of spatial neighbourhood in image processing reflects the fact that geometrically close pixels belong to the same structure or details, highly correlated and fall into the same cluster of the local histogram belonging to the central pixel. In order to extract the local histogram and overcome the drawback of blurring edges in most digital images, spatially adaptive iterative filtering techniques were developed. They hinged on non-stationary image models and utilized local statistics of the image to improve its form [61-62]. These techniques operate in the spatial domain and apply some local operations to perform noise smoothing without any specific assumption about signal and noise models. Their common concerns are the suppression of noise corruption and the preservation of image details in the distorted observation. Spatially Adaptive Iterative Filtering also uses the non-parametric restoration framework with spatially adapted transform through optimized iteration which is implemented patch-wise to carry out automatic adjustment of the local smoothing strength according to local signal-to-noise ratio (SNR). A block diagram of a typical spatially adaptive iterative filtering algorithm is presented in Fig. 7 [63-64].

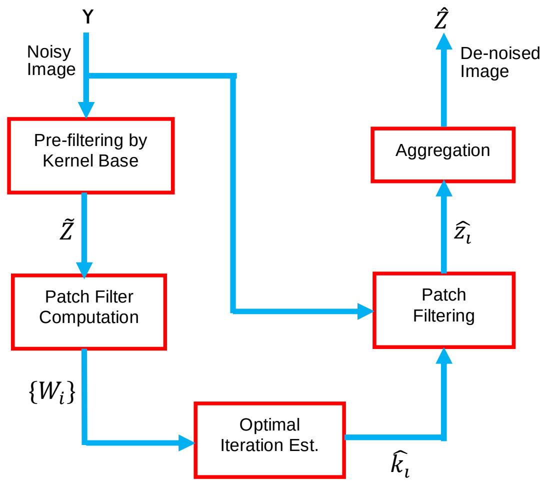

Fig. 7. Diagram of SAIF Algorithm

Starting from the noisy image Y and splitting it into N overlapping patches, $\{y_i\}_{i=1}^{N}$, each noisy patch y_i , is de-noised separately. To calculate the local filter patch W_i, an estimated image $\tilde{Z}$ filtered by the standard kernel baseline is used and then the estimation of the Mean Square Error (MSE) for the two iteration approaches (diffusion and boosting) for each patch is performed. By comparing their values, the optimal iteration method and consequently the iteration number $\hat{k_i}$ is selected, generating the filtered patch $\hat{z_i}$. Since these filtered patches are overlapped, an aggregation method is finally carried out to compute the de-noised image $\hat{Z}$. The algorithm is suitable for use in GIS with its strong point lying in its ability to boost the performance of spatial domain filters in terms of percentage SNR (MSE) and subjective visual quality to near state-of-the-art through optimized iteration methods.

2.11 Multi-Frame Super-Resolution

Multi-frame super-resolution is used to remove the main computational bottleneck associated with some other algorithms. It uses a known vectorized scene x of size $N \times 1$ and a given registration vector $\theta^{(k)}$ to generate a vectorized low-resolution image $y^{(k)}$ with M pixels through a system matrix $W^{(k)}$. Gaussian noise with precision β is then added to $y^{(k)}$ as follows [65]:

$$y^{(k)} = \rho_\alpha^{(k)} W\left(\theta^{(k)}\right) \mathrm{x} + \rho_\beta^{(k)} + \epsilon^{(k)} \quad (32)$$

$$\epsilon^{(k)} \sim \mathrm{N}\left(0, \beta^{-1}\mathrm{I}\right) \quad (33)$$

Photometric parameters ρ_α and ρ_β are used to provide a global affine correction for the scene illumination. ρ_β is simply an $M \times 1$ vector filled out with the value of ρ_β while each row of W(k) constructs a single pixel in $y^{(k)}$, and the row's entries are the vectorized and point-spread function (PSF) response for each low-resolution pixel, in the frame of the super-resolution image. The PSF is usually assumed to be an isotropic Gaussian on the imaging plane, though for some motion models (such as planar projective) this does not necessarily lead to a Gaussian distribution on the frame of x. For an individual low-resolution image, given registrations and x, the data likelihood is obtained from:

$$\mathrm{p}\left(y^{(k)}\middle|\mathrm{x}, \theta^{(k)}, \rho^{(\mathrm{k})}\right) = \left(\frac{\beta}{2\pi}\right)^{0.5\mathrm{M}} \mathrm{e}^{\left\{0.5\beta||y^{(k)} - \rho_{\alpha}^{(\mathrm{k})} W(\theta^{(k)})\, \mathrm{x} - \rho_{\beta}^{(\mathrm{k})}||_2^2\right\}} \tag{34}$$

When the approximation of the registration is determined, for instance by pre-registering inputs, the uncertainty can be modelled as a Gaussian perturbation about the mean estimate $\bar{\theta}^{(k)}$ for each image's parameter set. This technique was developed as an alternative approach for Bayesian image super-resolution with several advantages over some existing methods such as Tipping and Bishop's algorithm [66]. The use of a much more realistic image prior also reduces computational speed and memory efficiency relating to the smaller dimension.

3 Some Image Enhancement Works

Several proven and established works that are based on the algorithms presented in Section 2 have been done on digital image enhancement. They include mean-squared error-based iterative method [67]; iterative, adaptive and non-parametric regression [68], iterative guided filtering [63,69], maximum a priori (MAP) and Bayesian Integration [70] and Space-Invariant Deconvolution [71]. The authors in [39] applied range compression, contrast stretching, histogram equalization and noise smoothing algorithms for the enhancement of common digital images while Far Distance Filter (FDF) and Near Distance Filter (NDF) with (5 x 5) kernel were used for the enhancement of abnormal image pixels in [72]. A technique for improving the image quality of complementary metal-oxide semiconductor (CMOS) image sensor is presented in [49]. The technique compresses the image dynamic range, reorganizes its signal to improve visibility, suppresses noise, identifies local features and performs rendition of colour constancy and lightness.

An image resolution enhancing technique based on extracted 1-dimensional characteristic curves from frames and sub-pixel displacement values is given in [24]. Through sub-pixel mapping and adaptive interpolation, high-resolution image is obtained from several low-resolution frames. A digital image enhancement algorithm that is based on the concept of histogram equalization and contrast stretching is presented in [73]. The algorithm uses different procedures which encompass locally varying enhancement techniques for optimum display of different feature classes in an image. Different spectral bands were selected from storage of a priori knowledge in geographic information system (GIS) and context based image information through segmentation process. The authors in [74] formulated a generalized iterative fuzzy algorithm that is based on the statistical features of the gray-level histogram to enhance degraded and inaccurate image edges while a spatial domain technique that is based on fuzzy concepts such as histogram distribution analysis and smoothing techniques is proposed for image enhancement in [75]. A colour image enhancement technique based on the equalization of three 2-D histograms built with the RGB colour channels is proposed in [37]. The technique has square complexity of time and space irrespective of the number of levels in each channel. The technique proposed in [38] uses parameter-controlled virtual histogram distribution method and is driven by global and local processes on luminance and chrominance components of an image. It increases the visibility of specified portions of an image with good maintenance of colour.

The authors in [76] introduced a directional wavelet transform-based image enhancement technique that uses scale and directional information to decompose an image into four-dimensional space and augments. Multi-scale singularity detection is also used with adaptive threshold whose value is calculated via maximum entropy measure. Transform and spatial domain techniques of image enhancement were presented by the authors in [44] for addressing the limitations of the former. A technique which combines logarithmic and power law transforms with alpha rooting algorithm for robust contrast enhancement is also presented. The authors in [77] proposed a Laplacian like image-scale pyramid–based method for enhancing a fingerprint image. The method decomposes the original fingerprint into 3 smaller images corresponding to different frequency bands and contextual filtering was performed by using pyramid levels and 1-D Gaussians. A screen mammogram image denoising and enhancement technique that is based on Orthogonal Polynomial Transformation (OPT) is proposed in [78]. The technique scales a set of OPT edge coefficients to an inverse transformed set to obtain contrast improved image. In [11], the authors presented a curvelet transform for resolving over and under illumination problems in dimensional images through morphological transformations and closing through reconstruction.

The effect of noise on images is reduced by using Algebraic Reconstruction Technique (ART) and its variant discrete methods in [8]. The authors in [79] proposed an algorithm that is based on no-reference metric Q and singular value decomposition of local gradient matrix for image enhancement. The algorithm provides cheap and rapid response computation for quantitative measure of true sharpness and contrast in visually salient geometric features such as edges in the presence of noise and other disturbances. A platform for surface reconstruction and image enhancement via L1-minimization is presented with interior-point algorithm for solving the associated linear programming problem in [80]. The authors in [81] proposed a new technique that is based on statistical differencing for contrast enhancement of satellite images. The technique controls the sharpening effect by using two constants in such a way that enhancement occurs in intensity edges and uniform areas. A clustering-based image de-noising technique that uses locally learned dictionaries of the clusters of similar geometric structure is presented in [82]. The technique uses local weight functions with great information and robustness to convey image local structure even in the presence of significant amounts of noise. Each region (or cluster) was modelled using principal components analysis by "learning" the best basis which describes the patches within the cluster. Kernel regression-based dictionaries were also used for the optimal estimation of the underlying pixel values.

The authors in [43] presented an anisotropic diffusion Partial Differential Equation (PDE) model with Perona–Malik equation technique for the preservation and enhancement of image edges. The technique uses self-organizing maps and Bayesian inference to obtain accurate definition of difficult textural edge probabilities. A fuzzy measure theory for representing human subjectivity aggregated with objective criteria by fuzzy integrals is presented in [83]. Dempster aggregation rule was used to define the degree of compromise with a fuzzy rule-based approach for constructing an aggregation matrix that allows the generation of enhanced quality of portal images used in radiation therapy. Imaging geometry was used to propose an enhancement method for colour retinal images, with emphasis on contrast improvement devoid of artifacts in [6]. Non-uniform sampling was used to estimate the degradation and derive a correction factor from a single plane. A scheme for applying the derived factor to enhancing all the colour planes of a given image was also proposed. An image de-blurring technique based on Regularized Locally

Adaptive Kernel Regression (RLAKR) is proposed in [84]. The technique uses kernel regression for image enhancement and performs de-noising and de-blurring simultaneously based on an effective and novel image prior.

A Bayesian image resolution enhancement technique that marginalizes over the unknown registration parameters which relate with the set of input low-resolution views is presented in [65]. Illumination components were introduced into the generative model to handle changes in lighting as well as motion. A framework for image enhancement via Calibrated Lens Simulations (CLS) and Point Spread Function (PSF) is presented in [85]. A calibrated model computes the PSF for any desired setting of lens parameters for a scene depth, without additional measurements or calibration. The authors in [86] addressed the problem of incorporating user preference in automatic image enhancement by formulating active sensor selection and distance metric learning-based method for observing user preferences on training set and then learn a model of these preferences to personalize enhancement of unseen images. A system for scanning and enhancement of the visual quality of the content on a whiteboard is presented in [7]. The system automatically locates the boundary of a whiteboard, crops out and rectifies its region and corrects the board to completely white. A feature-based technique for automatically stitching multiple overlapping images arising from insufficient single image produced with low-resolution camera from large whiteboard is also proposed. Table 1 shows further, the summary of some of these works.

Table 1. Summary of some existing works on digital image enhancement

Research	**Methodology**	**Strength**	**Weakness**
Cristobal and Navarro, 1994 [4]	• Gabor and pyramidal representation	• Removal of degradation due to large amount of space and frequency variant fractal noise in medical images	• Performance diminishes with images with substantial amount of noise
Koo and Kim, 1999 [24]	• Extraction of 1-dimensional characteristics curve, sub-pixel interpolation	• Upgrades low resolution digital image to high resolution, • Applicable in real-time processing	• Unable to handle images in consumer and medical applications
Hamid and Bernd, 1999 [83]	• Fuzzy and Dempster aggregation rules	• Reliably enhanced portal images used in radiation therapy	• Unable to handle additive or fusion images • Computational complexities
Hammadou and Bouzerdoum, 2001 [49]	• Shunting inhibiting cellular neural networks	• Efficiently enhanced images from CMOS sensors	• It failed with other modules such as automatic gain and exposure control
Menoti et al., 2006 [37]	• 2-D histogram equalization	• Good for colour image enhancement	• Requires square complexity of time and space.
Heric and Potocnik, 2006 [76]	• Directional Wavelet Transform	• It uses multi-scale singularity detection	• Failed with images whose adaptive

		with adaptive threshold for enhancing images	threshold is not determinable
Pickup et al., 2007[65]	• Bayesian marginalization within the super-resolution model • Maximum a prior estimate	• Significantly improved fixed-registration approach in terms of computational speed and memory efficiency	• Its performance with domain-specific image prior is uncertain
Nadernejad et al., 2008 [10]	• Second, fourth and complex order Partial Differential Equation	• Strong for de-noising almost all types of digital image	• Failed with image with unpredictable noise level
Karras and Mertzios, 2009 [43]	• Partial Differential Equation, self-organizing feature map and Bayesian inference	• Very good for image filtering and restoration applications	• Computationally expensive
Zhengya et al., 2010 [38]	• Virtual histogram equalization	• Speedy and simultaneous enhancement of image overall contrast and sharpness	• Its performance depends on parameters whose determination are complex
Preethi and Rajeswari, 2010 [39]	• Range compression, contrast stressing, histogram equalization	• Good for enhancement of colour and gray scale medical images	• It experiences failure with image containing highly corrupt regions
Hantos and Balazs, 2010 [8]	• Median filters, algebraic reconstruction	• Enhances images typically degraded by salt and pepper-like noise	• Finding proper filter parameter strictly dependent on the type of image
Ahmed, 2011 [72]	• Spatial filters	• Image de-noising through removal of abnormal pixels	• Its lacks the threshold and kernel cardinality constraints
Arun et al., 2011 [44]	• Alpha rooting	• Efficiently enhance low contrast images arising from graying, tonal changes and artifacts	• Strictly rely on parameters whose computation is complex
Seo and Milanfar, 2012 [69]	• Guided filter kernel • Nonlinear anisotropic and reaction diffusions	• Suitable for use in flash/no-flash image denoising *and* deblurring,	• Strictly rely on the use of guided filters
		• Yields outputs that preserve fine details of the flash image and the ambient lighting of the no-flash image.	

Zhu and Milanfar, 2013 [71]	• Geometric deformation through B-spline-based non-rigid registration. • Regression process • A blind de-convolution algorithm	• Corrects geometric distortion and reduces space and time-varying blur	• Uses a number of parameters which are determined through computationally expensive processes.
Talebi and Milanfar, 2013 [64]	• Iterative filtering of local image content using base filter	• Significantly relax the base algorithm's Sensitivity to its tuning (smoothing) parameters • Greatly boost the performance of other denoising filters.	• Its performance diminishes for images with varied noise level across the whole image.
Talebi and Milanfar, 2014 [63]	• Spectral (principal) components estimation using the Nystrom extension.	• Effectively eliminate the issues of diminishing returns associated to increased patches in other patched based algorithms	• Computationally complex, • Strictly based on exploiting similarity between a relatively modest number of patches

4 Notable Specific Applications of Digital Image Enhancement

The following are some of the specific applications of digital image enhancement [37,72,75,77,87].

4.1 Geographic Information System (GIS)

Geographic images are extensively used in several navigational and mapping software packages including Google Earth and Microsoft Virtual Earth. These packages provide very rich geospatial or satellite images on transportation, traffic, terrain, places and so on. One of the several issues militating against effective and adequate utilization of these images is discrepancy in colour tone arising from inconsistencies in brightness, saturation or colour imbalance between images that represent adjacent areas [67]. The main effect of these inconsistencies is significant difference in the appearance of adjacent areas. Image enhancement is therefore consequently applied to eliminate these effects and for easier interpretation of image data. Commonly known image enhancement techniques in GIS include contrast stressing, edge enhancement and derivation of new data from the difference estimates ratio and other qualities from reflectance values in two or more bands, among several others. Physical and psychological experiments have shown that images with enhanced edges experienced visual satisfaction than images from exact reproduction [81].

4.2 Medical

Identifying the edges of low contrast structure is one of the salient tasks in the interpretation of medical images. Low contrast structures need to be resolved in computed tomography (CT), magnetic resonance (MR), digital mammography, ultrasound and angiography and nuclear medicine images. Getting a high contrast image directly from the imaging devices is in most cases expensive in examination time or X-ray. For instance, the low contrast in CT is merely increased by raising the number of photons absorbed in each voxel, which is proportional to the X-ray dose [3]. Therefore, while most medical images possess important structures with low natural contrast with the surrounding structures, the production of these images generally involves a compromise between the need for enhanced contrast and the various costs of obtaining it. In this case, enhancement via digital post processing is often employed.

4.3 Pattern Recognition and Matching

Most of the existing pattern recognition and matching systems require robust automatic identification and verification mechanisms that rely on accurate image acquisition and enhancement. In view of the fact that it is practically impossible to acquire noise free images at most times, the problem of poor quality consistently emerge necessitating the inclusion of preprocessing step of enhancement as a prelude to quality features extraction.

4.4 Visualization

It is noted that still images and video systems are typically limited in use with poor visibility conditions such as rain, fog, smoke and haze which severely limit the range, soundness and effectiveness of imaging systems. Several visual information processing groups including Space Research Centers, Weather Forecasters and Air Traffic Controllers have therefore developed image enhancement technologies of different concepts with direct applications on the problem of poor visibility conditions.

4.5 Security

Different dimensions have been taken towards ensuring suitable systems for securing lives and properties at private and public places across the world. A number of human traffic control and monitoring devices had been developed and equipped with image enhancement components for optimal performance. For instance, most surveillance systems have image enhancement capabilities as a measure for timely analysis and interpretation of recorded images in all conditions of weather and atmosphere. The latent fingerprint enrolled at crime scene is also enhanced for reliable feature extraction and pattern matching.

5 Conclusion

The review of several of the existing methods for digital image enhancement has been presented. The methods include Directional Wavelet Transform, Algebraic Reconstruction Model, Partial Differential Equation, Histogram Equalization and Cellular Neural Networks. Others are Adaptive Interpolation Method, Contrast Stretching, Range Compression, Alpha Rooting, Spatially

Adaptive Iterative Filtering and Multi-Frame Super Resolution. The application areas, strengths and weaknesses of these methods were discussed with features that determine their suitability for one application or the other. A review of some recent image enhancement works that are premised on these methods as well as some specific application areas of digital image enhancement were also presented. Future research aims at using the experimental study and integration of some of these methods as bases for obtaining an image enhancement technique with greater performance and acceptability in several applications.

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Competing Interests

Authors have declared that no competing interests exist.

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