



Image Enhancement by Local Operators

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Abstract— *Medical image is never the correct representation of the object under observation; it is always ruined by degradations during acquisition and within the imaging system itself. These include noise, distortion and smudge. Enhancement of such corrupted images is an important and challenging issue in medical image processing. These local operations on medical imaging have their own assumptions, advantages and disadvantages. This paper has been discussed and applied the local operators for the removal of noise from the medical images.*

Keywords— *Mean, Median, noise, kernel, histogram, enhancement.*

I. INTRODUCTION

Image enhancement is the processing of images to improve their appearance to human viewers, in terms of better contrast and visibility of features of interest, or to enhance their performance in subsequent computer-aided analysis and diagnosis. Because the objective of image enhancement is dependent on the application context and is often poorly defined, and the criteria are often subjective, image enhancement techniques tend to be ad hoc. Enhancement techniques[1] include point operations[2], where the output pixel value depends only on its corresponding input value, and local or neighbourhood operations, where the eventual output pixel value depends on the neighbourhood of input pixel values. These latter operations include convolution, which uses appropriate masks or kernels to produce smoothing or sharpening of an image.

Image enhancement techniques are mathematical techniques[1,2] that are aimed at realizing improvement in the quality of a given image. The result is another image that demonstrates certain features in a manner that is better in some sense as compared to their appearance in the original image. One may also derive or compute multiple processed versions of the original image, each presenting a selected feature in an enhanced appearance. Simple image enhancement techniques are developed and applied in an ad hoc manner. Advanced techniques that are optimized with reference to certain specific requirements and objective criteria are also available.

Although most enhancement techniques are applied with the aim of generating improved images for use by a human observer, some techniques are used to derive images that are meant for use by a subsequent algorithm for computer processing. Examples of the former category are techniques to remove noise, enhance contrast, and sharpen the details in a given image. The latter category includes many techniques in the former, but has an expanded range of possibilities, including edge detection and object segmentation. If used inappropriately, enhancement techniques themselves may increase noise while improving contrast, they may eliminate small details and edge sharpness while removing noise, and they may produce artifacts in general. Users need to be cautious to avoid these pitfalls in the pursuit of the best possible enhanced image.

Image enhancement[1] can only improve and clarify information that is already present in an image: it cannot recover what was never there in the first place! Therefore, at the stage of image capture it is essential to seek the best image quality by suitable sample preparation, adjustment of instrumentation, choice of lighting, etc. We state this as a principle:

II. LOCAL OPERATORS

Local operators[2] enhance the image by providing a new value for each pixel in a manner that depends only on that pixel and others in a neighborhood around it. Many local operators are linear spatial filters implemented with a kernel convolution, some are nonlinear operators, and others impart histogram equalization within a neighborhood. In this section we present a set of established standard filters commonly used for enhancement. They can be easily extended to obtain slightly modified results by increasing the size of the neighborhood while maintaining the structure and function of the operator.

A. Noise Suppression by Mean Filtering

Mean filtering can be achieved by convolving the image with a $(2K + 1 \times 2L + 1)$ kernel where each coefficient has a value equal to the reciprocal of the number of coefficients in the kernel. For example, when $L = K = 1$, we obtain

$$w(K,L) = \begin{matrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{matrix}$$

referred to as the 3×3 averaging kernel or mask[4]. Typically, this type of smoothing reduces noise in the image, but at the expense of the sharpness of edges [4, 5]. Examples of the application of this kernel are seen in Figure 1(a-d). Note that the size of the kernel is a critical factor in the successful application of this type of enhancement. Image details that are small relative to the size of the kernel are significantly suppressed, while image details significantly larger than the kernel size are affected moderately. The degree of noise suppression is related to the size of the kernel, with greater suppression achieved by larger kernels.

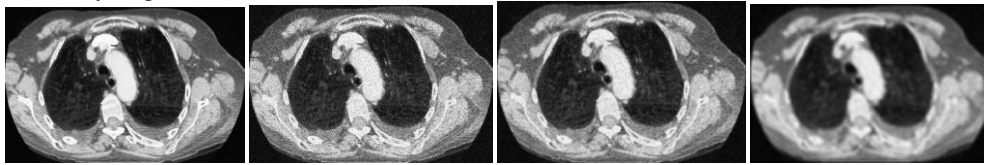


FIGURE 1 (a) Original CT image. (b) Original image in (a) corrupted by added Gaussian white noise with maximum amplitude of ± 25 gray levels. (c) Image in (b) convolved with the 3×3 mean filter. The mean filter clearly removes some of the additive noise; however, significant blurring also occurs. This image would not have significant clinical value. (d) Image in (b) convolved with the 9×9 mean filter. This filter has removed almost all the effects of the additive noise

B. Noise Suppression by Median Filtering.

Median filtering is a common nonlinear method[6,7] for noise suppression that has unique characteristics. It does not use convolution to process the image with a kernel of coefficients. Rather, in each position of the kernel frame, a pixel of the input image contained in the frame is selected to become the output pixel located at the coordinates of the kernel center. The kernel frame is centered on each pixel (m, n) of the original image, and the median value of pixels within the kernel frame is computed. The pixel at the coordinates (m, n) of the output image is set to this median value. In general, median filters do not have the same smoothing characteristics as the mean filter[1,6,7]. Features that are smaller than half the size of the median filter kernel are completely removed by the filter. Large discontinuities such as edges and large changes in image intensity are not affected in terms of gray-level intensity by the median filter, although their positions may be shifted by a few pixels. This nonlinear operation of the median filter allows significant reduction of specific types of noise. For example, “pepper-and-salt noise” may be removed completely from an image without attenuation of significant edges or image characteristics. Figure 2 presents typical results of median filtering.



FIGURE 2 (a) Image in Figure 1(b) enhanced with a 3×3 median filter. The median filter is not as effective in noise removal as the mean filter of the same size; however, edges are not as severely degraded by the median filter. (b) Image in Figure 1(a) with added “pepper-and-salt” noise. (c) Image in Figure 2(b) enhanced by a 3×3 median filter. The median filter is able to significantly enhance this image, allowing almost all noise to be eliminated

C. Edge Enhancement

Edge enhancement in images is of unique importance because the human visual system uses edges as a key factor in the comprehension of the contents of an image. Edges in different orientations can be selectively identified and enhanced. The edge-enhanced images may be combined with the original image in order to preserve the context

Horizontal edges and lines are enhanced with

$$wH1(k, l) = \begin{cases} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \\ wH1(k, l) = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \end{cases}$$

and vertical edges and lines are enhanced with

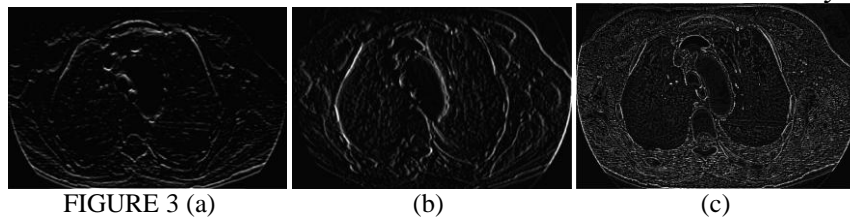
$$wV1(k, l) = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} \quad wH1(k, l) = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

The omni-directional kernel (unsharp mask) enhances edges in all directions:

$$KHP(k, l) = \begin{bmatrix} -1/8 & -1/8 & -1/8 \\ -1/8 & 1 & -1/8 \\ -1/8 & -1/8 & -1/8 \end{bmatrix}$$

The application of these kernels to a positive-valued image can result in an output image with both positive and negative values. An enhanced image with only positive pixels can be obtained either by adding an offset or by taking the absolute value of each pixel in the output image. If we are interested in displaying edge-only information, this may be a good approach. On the other hand, if we are interested in enhancing edges that are consistent with the kernel and suppressing those that are not, the output image may be added to the original input image. This addition will most likely result in a nonnegative image.

This is accomplished in one step by convolving the original image with the kernel after adding 1 to its central coefficient. Edge enhancement appears to provide greater contrast than the original imagery when diagnosing pathologies.



III. LOCAL-AREA HISTOGRAM EQUALIZATION

A remarkably effective method of image enhancement is local area histogram equalization, obtained with a modification of the pixel operation. Local-area histogram equalization applies the concepts of whole-image histogram equalization to small, overlapping local areas of the image. It is a nonlinear operation and can significantly increase the observability of subtle features in the image. The method formulated as shown next is applied at each pixel (m,n) of the input image:

A. Histogram Equalization

A popular general-purpose method of image enhancement is histogram equalization[1,5]. In this method, a monotonically increasing transformation function, $T(r)$ is used to map the original gray values, r_i of the input image into new gray values, s_i of the output image such that:

$$s_i = T(r_i) = \sum_{j=0}^i p_r(r_j) = \sum_{j=0}^i \frac{n_j}{n} \quad \text{for } i = 0, 1, \dots, L - 1, \quad (1)$$

where $p_r(r_i)$ is the probability based histogram of the input image that is transformed into the output image with the histogram $p_s(s_i)$.

The transformation function $T(r_i)$ in Eq. (1) stretches the histogram of the input image such that the gray values occur in the output image with equal probability of occurrence. It should be noted that the uniform distribution of the histogram of the output image is limited by discrete computation of the gray-level transformation[8,9]. The histogram equalization[1,5,18,23] method forces image intensity levels to be redistributed with an equal probability of occurrence. Figure 4 shows the original mammogram image and its histogram equalized image with their respective histograms. Image saturation around the middle of the image can be noticed in the histogram equalized[1,10] image.

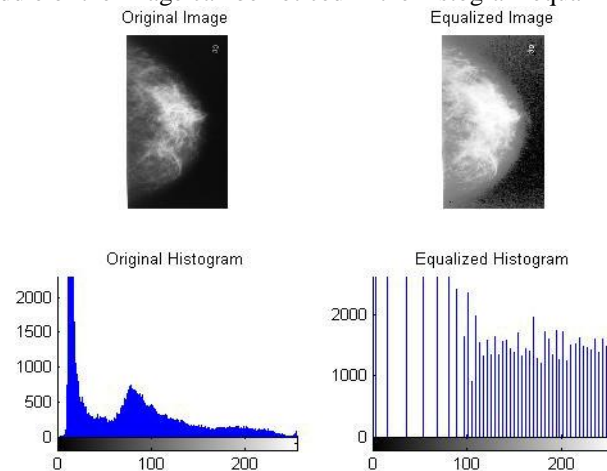


Fig. 4: Top left: original X-ray mammogram image; Bottom left: histogram of the original image; Top right: the histogram equalized image; Bottom right: histogram of the equalized image.

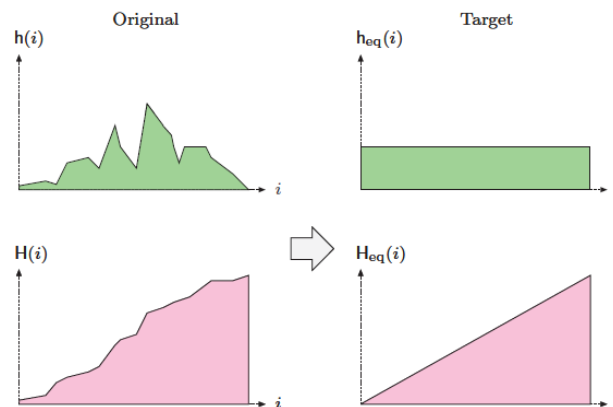


Figure5: Histogram equalization. The idea is to find and apply a point operation to the image (with original histogram h) such that the histogram h_{eq} of the modified image approximates a uniform distribution (top). The cumulative target histogram H_{eq} must thus be approximately wedge-shaped (bottom).

The goal of histogram equalization is to find and apply a point operation such that the histogram of the modified image approximates a *uniform* distribution (see Fig.5). Since the

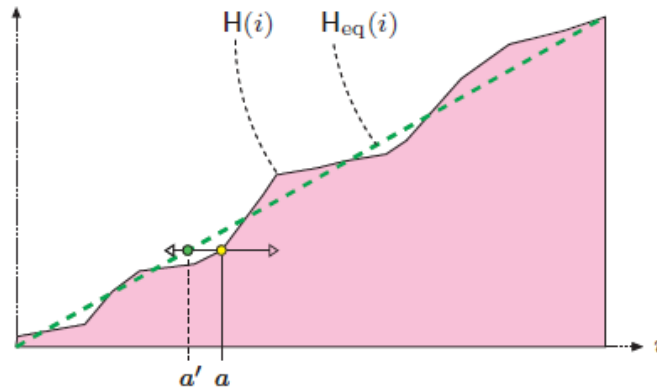


Figure 6: Histogram equalization on the cumulative histogram. A suitable point operation $a' \leftarrow \text{feq}(a)$ shifts each histogram line from its original position a to a' (left or right) such that the resulting cumulative histogram H_{eq} is approximately linear.

histogram is a discrete distribution[13] and homogeneous point operations can only shift and merge (but never split) histogram entries, we can only obtain an approximate solution in general. In particular, there is no way to eliminate or decrease individual peaks in a histogram, and a truly uniform distribution is thus impossible to reach. Based on point operations, we can thus modify the image only to the extent that the resulting histogram is *approximately* uniform.

The question is how good this approximation can be and exactly which point operation (which clearly depends on the image content) we must apply to achieve this goal. We may get a first idea by observing that the *cumulative* histogram[15] of a uniformly distributed image is a linear ramp (wedge), as shown in Fig. 5. So we can reformulate the goal as finding a point operation that shifts the histogram lines such that the resulting cumulative histogram is approximately linear, as illustrated in Fig. 6.

Histogram Modification

The histogram equalization method stretches the contrast of an image by redistributing the gray values to achieve a uniform distribution[5]. This general method may not provide good results in many applications. It can be noted from Fig. 4 that the histogram equalization method can cause saturation in some regions of the image resulting in loss of details and high-frequency information that may be necessary for interpretation. Sometimes, local histogram equalization[1,15] is applied separately on predefined local neighborhood regions, such as 7×7 pixels, to provide better results. If a desired distribution of gray values is known *a priori*, a histogram modification method is used to apply a transformation that changes the gray values to match the desired distribution. The target distribution can be obtained from a good contrast image that is obtained under similar imaging conditions. Alternatively, an original image from a scanner can be interactively modified through regional scaling of gray values to achieve the desired contrast. This image can now provide a target distribution to the rest of the images, obtained under similar imaging conditions, for automatic enhancement using the histogram modification method.

The conventional scaling method of changing gray values from the range $[a, b]$ to $[c, d]$ can be given by a linear transformation as:

$$z_{new} = \frac{d-c}{b-a}(z-a) + c \quad (2)$$

where z and z_{new} are, respectively, the original and new gray values of a pixel in the image.

Let us assume that $p_z(z_i)$ is the target histogram expressed, and $p_r(r_i)$ and $p_s(s_i)$ are, respectively, the histograms of the input and output image. A transformation is needed such that the output image $p_s(s_i)$ should have the desired histogram of $p_z(z_i)$. The first step in this process is to equalize $p_r(r_i)$ using the Eq. 1 such that

$$u_i = T(r_i) = \sum_{j=0}^i p_r(r_j) \quad \text{for } i = 0, 1, \dots, L-1 \quad (3)$$

where u_i represents the equalized gray values of the input image. A new transformation V can be defined to equalize the target histogram such that:

$$v_i = V(z_i) = \sum_{j=0}^i p_z(z_k) \quad \text{for } i = 0, 1, \dots, L-1 \quad (4)$$

Putting $V(z_i) = T(r_i) = u_i$ to achieve the target distribution, new gray values s_i for the output image are computed from the inverse transformation V^{-1} as:

$$s_i = V^{-1}[T(r_i)] = V^{-1}(u_i). \quad (5)$$

With the transformation defined in Eq. 5, the histogram distribution of the output image $p_s(s_i)$ would become similar to that of p_z .

IV. RESULT AND DISCUSSION

Fig 1(a) is the original CT image where gray levels are not uniformly distributed. This image is corrupted by added Gaussian white noise with maximum amplitude of ± 25 gray levels. A 3×3 median filter has been applied on this corrupt image, results gets the improved image in 1(c). The mean filter clearly removes some of the additive noise; however,

significant blurring also occurs. This image would not have significant clinical value. 1(d) Image in (b) convolved with the 9×9 mean filter. This filter has removed almost all the effects of the additive noise. In another experiment with the mean filter, the corrupted image of 1(b) is enhanced with the 3×3 median filter, resulting the image of 2(a). The median filter is not as effective in noise removal as the mean filter of the same size; however, edges are not as severely degraded by the median filter. (b) Image in Figure 1(a) with added "pepper-and-salt" noise. (c) Image in Figure 2(b) enhanced by a 3×3 median filter. The median filter is able to significantly enhance this image, allowing almost all noise to be eliminated. Figure 3 illustrates enhancement after the application of kernels w_{H1} , w_{V1} , and w_{HP} to the images in Figure 1(a). Figures 3(a), 3(b), and 3(c) show the absolute value of the output images obtained with w_{H1} , w_{V1} , and w_{HP} , respectively applied to the CT image. Hence it is concluded that the local operators are very useful for enhancing the image quality of the medical images for better diagnosis of the patient.

REFERENCES

- [1] Rafael C. Gonzalez University of Tennessee, Richard E. Woods. Digital image processing Third Edition 2008 .Pearson Education.
- [2] Rafael C. Gonzalez University of Tennessee, Richard E Woods, Steven L. Eddins. Digital image processing using MATLAB. Fourth impression 2008 .Pearson Education.
- [3] Anke Meyer-Base. Pattern recognition for medical imaging 2004. Elsevier academic press.
- [4] Bernard Jahn. Digital image processing, fifth revised edition. Springer-Verlag Berlin Heidelberg New York.
- [5] Roger Bourne ,Fundamentals of Digital Imaging in Medicine by Springer-Verlag London Limited 2010.
- [6] Geoff Daugherty, Digital Image Processing for Medical Applications, Cambridge University Press 2009.
- [7] Atam P Dhawan, H K Huang, Day-Shik Kim. Principles And Advance Method In Medical Imaging And Image Analysis, World Scientific Publishing Co. Pvt. Ltd 2008.
- [8] Issac h Bankman Handbook of medical image processing and analysis, Elsevier Inc 2009.
- [9] J.C. Russ, The Image Processing Handbook (fifth edition), CRC Press, 2007.
- [10] Sankar Seramani, Zhou Jiyan. "Denoising of MR images using non linear anisotropic diffusion filtering as a preprocessing steps". http://www.ijbst.org-a.googlepages.com/IJBST_1_1_17-21.pdf IJBST (2008), 1(1):17-21.
- [11] Tarek A Mahmoud, Stephen Marshall. Medical image enhancement using threshold decomposition driven adaptive morphological filter. 16th European Signal Processing Conference (EUSIPCO 2008), Lausanne, Switzerland, August 25-29, 2008.
- [12] Muhammad luqman bin muhd Jain. Enhancement of bone fracture image using filtering techniques. The International Journal of Video & Image Processing and Network Security IJVIPNS Vol: 9 No: 10 pp 49-54.
- [13] Vivian E Pera, Erica L. Heffer, Spatial second-derivative image processing: an application to optical mammography to enhance the detection of breast tumors. Journal of Biomedical Optics 8(3), 517-524 (July 2003).
- [14] Mrs firouz Abdullah Al-Wassai, Dr. N V Kalyankar. Arithmetic and frequency filtering methods of pixel based image fusion techniques. IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 3, No. 1, May 2011.pp 113-122.
- [15] Hadi sadoghi Yazdi, Farank Homayouni. Impulsive noise suppression of images using adaptive median filter. International Journal of Signal Processing, Image Processing and Pattern Recognition. Vol. 3, No. 3, September, 2010. Pp 1-12.