ARTEFACT REMOVAL AND EDGE DETECTION FROM MEDICAL IMAGE

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ABSTRACT
Medical images obtained from devices such as Ultrasonography, X-Ray, CT and MRI exhibit diverse image characteristics but are essentially collection of intensity variations from which specific abnormalities are needed to be pre-processed and isolated. This paper proposes Artifact Removal algorithm and Edge Detection algorithm that is equally effective with most medical images.

KEYWORDS: Medical image, Radius bone, and Gray scale morphology.

INTRODUCTION
Medical imaging has been undergoing a revolution in the past decade with the advent of faster, more accurate and less invasive devices.

In breast cancer the purpose of pre-processing is to remove noise and radiopaque artefacts contained within the mammogram and increase region homogeneity, with the objective being to improve in algorithm reliability and robustness. Mammograms often contain artefacts in the form of identification labels, markers, and wedges in the unexposed air-background (non-breast) region. Such artefacts are usually radiopaque in the sense that they are not transparent to radiation.

Magnetic Resonance Imaging is considered very powerful diagnostic methods to detect any abnormalities. As in all imaging process, artefacts can occur, resulting in degraded quality of image which can compromise imaging evaluation. An artefact is a feature appearing in an image that is not present in the original object. Artefacts remain a problematic area in magnetic resonance imaging (MRI) and some affect the quality of the examination, while others may be confused with pathology. Depending on their origin, artefacts are typically classified as patient-related, signal processing dependent and hardware (machine)-related.

Pre-processing (artefact removal) techniques are used to improve the detection of the suspicious region from Magnetic Resonance Images (MRI). Thus a statistical method has been served to remove the artefact from MRI of brain image and the proposed method has been successfully implemented and produces very good results. This process helps to diagnosis any disease from MRI of brain. We no longer look to MR imaging to provide only structural information, but also functional information of various kinds such that information about blood flow, cardiac function, biochemical processes, tumour kinetics, and blood oxygen levels (for mapping of brain function). Magnetic resonance (MR) imaging creates images of atoms’ nuclei using the property of nuclear magnetic resonance. This allows MRI systems to extract more detailed information about the human body than is possible to get with X-rays. Artefacts occur in MR images in the presence of ferromagnetic metal.

For decades, computed tomography (CT) images have been widely used to discover valuable anatomical information. Metallic implants such as dental fillings cause severe streaking artefacts which significantly degrade the quality of CT images. Metallic implants in CT images cause dark and bright streaking artefacts because of the high atomic number of metal. Low-energy X-ray photons passing through these objects are highly attenuated and this leads to loss of projection data.

There are different types of artefacts that may corrupt the x-ray image. Some artefacts are caused by the patient itself. For example, the motion artefact which occurs when the patient moves during the acquisition, and the metal artefact which results from having metallic dental fillings or implants. Another type of artefact results from an x-ray source that emits x-rays of multiple energies. This is called a beam hardening artefact.

The electroencephalogram (EEG) represents the electrical activity of the brain recorded by placing
several electrodes on the scalp. While measuring the EEG, all of the signals are not contributed by the electrical activity of the brain. Many potential changes seen in the EEG may be from other sources. Artefacts are undesired signals that may introduce changes in the measurements and affect the signal of interest. Even if the ideal way of working with EEG signal is to avoid the occurrence of artefacts when recording the EEG signal is unfortunately often contaminated by various physiological factors other than cerebral activity, which are typically of non-interest. For instance, cardiac activity, ocular movements, eye blinks and muscular activity are among the most common types of artefacts.

Due to the sources of noise being very diverse and having different characteristics, most authors focus on removing single types of artefacts. The cancellation of noise and artefacts is an important issue in EEG signal processing and normally a prerequisite for the subsequent signal analysis to be more reliable. As a kind of physiological signals, the electroencephalogram (EEG) represents the electrical activity of the brain. Because of its higher time-varying sensitivity, EEG is susceptible to many artefacts, such as eye-movements, blinks, cardiac signals, muscle noise. These noises in recording EEG pose a major embarrassment for EEG interpretation and disposal. A number of methods have been proposed to overcome this problem, ranging from the rejection of various artefacts to the effect estimate of removing artefacts.

Diagnostic imaging is a vital tool in medicine today. These imaging techniques provide an effective means for non-invasive mapping of the anatomy of an organ of a patient. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and are a critical component in diagnosis and treatment planning. With the increasing size and number of medical images, the use of computers for processing and analysis of medical images has become necessary and critical. The relative change in size, shape and the spatial relationships between anatomical structures obtained from intensity distributions provide important information in clinical diagnosis for monitoring disease progression. Therefore, radiologists are particularly interested to observe the size, shape and texture of the organs and/or parts of the organ. The recognition, labelling and the quantitative measurement of specific objects and structures are involved in the analysis of medical images. To provide the information about an object clinically in terms of its morphology and anatomy, image segmentation and classification are important tools to obtain the desired information.

In medical images edge detection is an important work for object recognition of the human organs such as breasts. For mammograms manifesting masses this corresponds to the detection of suspicious mass regions. The work of the edge detection decides the result of the final processed image. Conventionally, edge is detected according to some early brought forward algorithms like Sobel algorithm, Prewitt algorithm and Laplacian of Gaussian operator, but in theory these operators belongs to the high pass filtering, which are not suitable for noisy images.

The medical image detection system consists of several phases. The first phase consists of capturing of the medical image by common capture devices like X-ray, MRI (Magnetic Resonance Imaging), CT (Computed Tomography), Mammographic Devices and Sonographer devices. In the next phase we need to convert the mode of medical image to grey scale image. Medical images from different devices show different intensities. We need to adjust the intensity to get a normalized intensity level. Then we need to apply an edge-detection filter on the image. In this paper, we have proposed a new edge-detection technique for mammographic images. We have compared the results obtained by our proposed method with other known methods of edge detection namely, Sobel, Prewit, Roberts, Kirsch and LoG edge detection filters. The final phase of the detection system is feature extraction. The objective of this process is to find the specification of the medical image and define the image morphology.

Process of identification of sharp discontinuities of an image is called edge of an image i.e., edges are significant local changes of intensity. Here discontinuities mean abrupt changes of pixel intensity of image in a scene. Thus intensity causes basically geometric events and non-geometric events; geometric events basically discontinuity in depth and/or colour and texture i.e., object boundary and discontinuity in surface and/or colour and texture i.e., surface boundary and non-geometric events basically direct reflection of light called specularity and inner reflection or shadows from other object or same object. In high level image vision, edge detection is used in the interpretation of 3D objects from 2D images obtained from an image occlusion in radiological imaging. The goal of edge detection is to produce a continuous line drawing of a scene from an image of that scene. Important features can be extracted from the edges of an image (e.g., corners, lines, curves) and these features are used by higher-level computer vision algorithms (e.g., recognition) for analysis.

Medical image analysis is critical in numerous biomedical applications such as detection of abnormalities, tissue measurement, surgical planning and simulation, and many more. In particular, image segmentation is an essential step, which partitions the medical image into different non-overlapping regions such that each region is nearly homogeneous and ideally corresponds to some anatomical structure or region of interest. It is the main tool in pattern recognition, object recognition, image restoration, image segmentation, and scene analysis. An edge detector is principally a high-pass filter that can be applied to extract the edge points in an image. Medical image are images of the human body
or parts of the body intended for clinical purposes or revealing or diagnosis of disease in medical science. Detection of edges in an image is a very important step towards understanding image features. Since edges often occur at image locations representing object boundaries, edge detection is extensively used in image segmentation when images are divided into areas corresponding to different objects. This can be used specifically for enhancing the tumour area in mammographic images. Different methods are available for edge detection like Roberts, Sobel, Prewitt, Kirsch and Laplacian of Gaussian edge operators. In this paper algorithm for artefact removal and algorithm for edge detection has been proposed for medical images.

REVIEW WORKS

Digital Mammogram is one of popular technique to identify breast cancer. Digital Mammography is the most effective and economical breast imaging modality due to its simplicity, portability and cost effectiveness. Breast cancer is a leading cause of cancer deaths among women. For women in US and other developed countries, it is the most frequently diagnosed cancer. In India, a death rate of one in eight women has been reported due to breast cancer. Breast cancer begins in breast tissue, which is made up of glands for milk production, called lobules and the ducts that connect lobules to the nipple.

Edge detection is a problem of fundamental importance in image analysis. In a typical image, edges characterize object boundaries and are therefore useful for segmentation, registration, and identification of objects in a scene.

Edge detection is one of the most commonly used operations in image analysis. An edge is defined by a discontinuity in gray level values. In other words, an edge is the boundary between an object and the background. The shape of edges in images depends on many parameters: The geometrical and optical properties of the object, the illumination conditions, and the noise level in the images. The importance of the classification is that it simplifies several problems in Artificial Vision and Image Processing, by associating specific processing rules to each type of edges.

In practice, sampling, and other image acquisition imperfections yield edges that are blurred, with the degree of blurring being determined by the factors such as quality of the image acquisition system, the sampling rate, and illumination conditions under which the image is acquired. As a result, edges are more closely modelled as having a "ramp like" profile. The slope of the ramp is inversely proportional to the degree of blurring in the edge. The blurred edges tend to be thick and sharp edges tend to be thin.

In order to improve the accuracy of interpretation, a variety of screening techniques have been developed. Recent studies showed that —the interpretation of the mammograms by the radiologists gave high rates of false positive cases. The images provided by different patients have different dynamics of intensity and present a weak contrast. Moreover the size of the significant details can be very small. Several research works have tried to develop fully automated computer aided diagnosis (CAD) tools that could help the radiologists in the interpretation of the mammograms and could be useful for an accurate diagnosis.

Prior to performing pre-processing on digital mammogram it is essential to understand the different types of artefacts and noise which are present within the breast and non-breast region of digital mammogram. While the incidence of artefact on digital mammographic images are typically less than with film based mammography, artefacts can be produced on digital systems. Van Ongeval et al have classified the artefacts in —clinical digital mammograms. Chaloeykitti L et al reviewed all the artefacts in mammography encountered classified the causes of these artefacts into four categories i.e. patient-related, technologist-related, related to the mammographic unit and related to processing and the processor.

Williams M B et al described in detail what is known to "improve image quality for digital mammography and make recommendations about how digital mammography should be performed to optimize the visualization of breast cancers. Bloomquist A K et al have presented a study on —standardization and comparison of image quality of full-field digital mammography (FFDM) versus screen-film mammography in a screening population. However, they found that it was difficult to standardize and compare these. Yaffe MJ et al recommended set of tests including additional and improved tests, which they believe —meet the intent and spirit of the Mammography Quality Standards Act regulations to ensure that full field digital mammography systems are functioning correctly and consistently producing mammograms of excellent image quality.

Rama S. Ayyala et al classified the artefact especially on digital mammogram. According to them —some of these artefacts are similar to those seen with screen-film mammography, many are unique to digital mammography—specifically, those due to software processing errors or digital detector deficiencies. In addition, digital mammographic artefacts depend on detector technology (direct vs indirect) and therefore can be vendor specific. It is important that the technologist, radiologist and physicist become familiar with the spectrum of digital mammographic artefacts and pay careful attention to digital quality control procedures to ensure optimal image quality.

Wirth et al have proposed one of the well-known artefact suppression algorithm based on —area
morphology to remove radiopaque artefacts from the background region of mammograms.

The large growth in MR imaging field is attributable to rapid technological advances in several areas, including magnet technology, gradient coil design, radiofrequency (RF) technology, and computer engineering. In stride with the rapid technological advances, there has been phenomenal growth in the number of applications for MR imaging. Artefacts remain a problematic area in magnetic resonance imaging (MRI). Depending on their origin, artefacts are typically classified as patient-related, signal processing dependent and hardware related. L.

J Erasmus[15] (2004) et. al. gives a very good description of different type of MRI artefacts. Bradley G. Goodyear et. al. in 2004[16] proposed a technique that based on the Stockwell transform (ST), a mathematical operation that provides the frequency content at each time point within a time-varying signal. Using this technique, 1D Fourier transforms (FTs) are performed on raw image data to obtain phase profiles and results; navigator echo correction is successful at removing phase fluctuations due to physiological processes such as respiration. The ST filter, on the other hand, does not perform well nor is it designed to alter phase oscillations at such low frequencies.

Qing X. Yang[17] in Removal of Local Field Gradient Artefacts in T2 Weighted Images at High Fields by Gradient Echo Slice Excitation Profile Image gives a idea to remove artefact using signal processing. Philip J. Allen[18] (2000) has developed a recording system and an artefact reduction method that reduce artefact effectively. The recording system has large dynamic range to capture both low-amplitude EEG and large imaging artefact without distortion 5-kHz sampling, and low-pass filtering prior to the main gain stage and validated in recordings from five subjects using two fMRI sequences by measurement of residual artefact, spectral analysis, and identification of spike-wave complexes in the corrected EEG.

Travis B Smith et. al (2010)[19] gives a design and scanning protocols which can prevent certain artefacts from occurring, but some are unavoidable. Numerous correction methods have been developed to mitigate the corrective effects of artefacts and improve image diagnostic quality. D. Mantiniet. al.[20] presented a comprehensive method based on independent component analysis (ICA) for simultaneously removing BCG and ocular artefacts from the EEG recordings, as well as residual MRI contamination left by averaged artefact subtraction. Sudipta Roy[21-22] et. al. proposed methods for brain tumour detection and use MRI of brain without artefact as an input. K. Selvanayaki et. al. proposed[23] a methods using based on the first derivative and local statistics but this methods does not produce good result for many images and some artefact also present after applying the methods. Thus artefact removal from MRI image is an important task.

Edge detection is a critical element in image processing, since edges contain a major function of image information. The function of edge detection is to identify the boundaries of homogeneous regions in an image based on properties such as intensity and texture. Many edge detection algorithms have been developed based on computation of the intensity gradient vector, which, in general, is sensitive to noise in the image. In order to suppress the noise, some spatial averaging may be combined with differentiation such as the Laplacian of Gaussian operator and the detection of zero crossing.

Combining both spatial and intensity information in image, we present an MRI brain image segmentation approach based on multi-resolution edge detection, region selection, and intensity threshold methods. The detection of white matter structure in brain is emphasized in this paper. First, a multi-resolution brain image representation and segmentation procedure based on a multi-scale image filtering method is presented. Given the nature of the structural connectivity and intensity homogeneity of brain tissues, region-based methods such as region growing and subtraction to segment the brain tissue structure from the multi-resolution images are utilized. From the segmented structure, the region-of-interest (ROI) image in the structure region is derived, and then a modified segmentation of the ROI based on an automatic threshold method using our threshold selection criterion is presented. Examples on both T1 and T2 weighted MRI brain image segmentation is presented, showing finer brain tissue structures.

There are many ways to perform edge detection. However, the most may be grouped into two categories, gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The Laplacian method searches for zero crossings in the second derivative of the image to find edges.

The facial features (eyes, nose, mouth) have very sharp edges. These also happen to be the best reference points for morphing between two images. Notice also that the Marr-Hildreth not only has a lot more noise than the other methods, the low-pass filtering it uses distorts the actual position of the facial features. Due to the nature of the Sobel and Prewitt filters we can select out only vertical and horizontal edges of the image as shown below. This is very useful since we do not want to morph a vertical edge in the initial image to a horizontal edge in the final image. This would cause a lot of warping in the transition image and thus a bad morph.

Canny[24] derived analytically optimal step edge operators and showed that the first derivative of Gaussian filter is a good approximation of such operators. An alternative to gradient techniques is based
on statistical approaches. The idea is to examine the distribution of intensity values in the neighbourhood of a given pixel and determine if the pixel is to be classified as an edge. In comparison with the differential approaches, less attention has been paid to statistical approaches. However, this method has been approached by some authors, e.g., Bovik et al.\(^{[26]}\) and Yakimovsky.\(^{[25]}\) In the past two decades several algorithms were developed to extract the contour of homogeneous regions within digital image. A lot of the attention is focused to edge detection, being a crucial part in most of the algorithms. Classically, the first stage of edge detection (e.g. the gradient operator, Robert operator, the Sobel operator, the Prewitt operator) is the evaluation of derivatives of the image intensity. Smoothing filter and surface fitting are used as regularization techniques to make differentiation more immune to noise. Raman Maini and J. S. Sobel\(^{[27]}\) evaluated the performance of the Prewitt edge detector for noisy image and demonstrated that the Prewitt edge detector works quite well for digital image corrupted with Poisson noise whereas its performance decreases sharply for other kind of noise.

Davis, L. S."\(^{[28]}\) has suggested Gaussian pre-convolution for this purpose. However, all the Gaussian and Gaussian-like smoothing filters, while smoothing out the noise, also remove genuine high frequency edge features, degrade localization and degrade the detection of low-contrast edges. The classical operators emphasize the high frequency components in the image and therefore act poorly in cases of moderate low SNR and/or low spatial resolution of the imaging device. The awareness of this has lead to new approaches in which balanced trade-offs are sought between noise suppression, edges, altogether resulting in operators acting like band-pass filters e.g. Canny.

Sharifi, M. et al.\(^{[29]}\) introduces a new classification of most important and commonly used edge detection algorithms, namely ISEF, Canny, Marr-ildreth, Sobel, Kirch and Laplacian. They discussed the advantages and disadvantages of these algorithms. Shin, M.C et al.\(^{[30]}\) presented an evaluation of edge detector performance using a structure from motion task. They found that the Canny detector had the best test performance and the best robustness in convergence and is one of the faster executing detectors. It performs the best for the task of structure from motion. This conclusion is similar to that reached by Heath et al.\(^{[31]}\) in the context of human visual edge rating experiment. Rital, S. et al.\(^{[32]}\) proposed a new algorithm of edge detection based on properties of hyper graph theory and showed this algorithm is accurate, robust on both synthetic and real image corrupted by noise. Li Dong Zhang and Du Yan Bi\(^{[33]}\) presented an edge detection algorithm that the gradient image is segmented in two orthogonal orientations and local maxima are derived from the section curves. They showed that this algorithm can improve the edge resolution and insensitivity to noise. Zhao Yu-qian et al.\(^{[34]}\) proposed a novel mathematic morphological algorithm to detect lungs CT medical image edge. They showed that this algorithm is more efficient for medical image denoising and edge detecting than the usually used template-based edge detection algorithms such as Laplacian of Gaussian operator and Sobel edge detector, and general morphological edge detection algorithm such as morphological gradient operation and dilation residue edge detector.

Fesharaki, M.N. and Hellestrand, G.R.\(^{[35]}\) presented a new edge detection algorithm based on a statistical approach using the students t-test. They selected a 5x5 window and partitioned into eight different orientations in order to detect edges. One of the partitioning matched with the direction of the edge in the image shows the highest values for the defined statistic in that algorithm. They show that this method suppresses noise significantly with preserving edges without a prior knowledge about the power of noise in the image. Algorithm can successfully discover edges for diverse images and no specific quantitative measure of the quality for edge detection is given at present.\(^{[36-37]}\)

**Proposed Method**

Many different artefacts can occur in medical image, some affecting the diagnostic quality, while others may be confused with pathology. The removal of artefact is also an important task in medical image analysis. In the subsequent paragraph both algorithms are presented along with the results.

**Algorithm for Artefact Removal**

**Step 1.** Grayscale medical image is taken as input.

**Step 2.** Threshold value of the image is calculated using the standard deviation technique described above.

**Step 3.** The image is binarized using the threshold value. i.e. pixels having value greater than the threshold is set to 1 and pixels less than the threshold are set to 0.

**Step 4.** The binarized image is labelled and areas of connected components are calculated using equivalence classes.

**Step 5.** The connected component with the maximum area and the connected component with the second highest area are found out.

**Step 6.** The ratio of the maximum area to that of second maximum area are calculated.

**Step 7.** On the basis of the ratio if ratio is high only the component with highest area is kept and all others are removed otherwise if ratio is low the component with the highest and second highest area are kept and all others are removed.

**Step 8.** A convex hull is calculated for the one pixel in
the image and all regions within the convex hull are set to one.

Step 9. Now the above obtained image matrix is multiplied to the original image matrix to obtain an image consisting of only medical image without any artefact.

Original MRI image with artefact is shown below.

*In figure below no artefact present i.e. all artefacts are removed by proposed algorithm.

Now a day’s artefacts are principally letter or metal related artefacts or Gibbs artefact. Letter artefact is present in most of the brain MRI images due to patient’s information being embedded in them. High quality of MRI machine ensures metal related and susceptibility artefact are very few.

Any grayscale image is represented as a two-dimensional array of pixel intensities. A grayscale image can be expressed as a combination of k intensity values with a certain frequency f(k) where k = 0 to n. In this research paper a new structure is proposed to represent images using a modified full and complete binary tree that will accommodate both the intensity and frequency measures. The objective in constructing such a tree is to obtain an image with reduced number of colour, yet maintaining the full colour palette; thus achieving colour quantization at every tree level. Results and algorithm are shown below.

Algorithm for Edge Detection

Algorithm
Basic functions are defined which are used in algorithms: Parent (i)

Return \[i/2\]
Left (i)
Return 2i
Right (i)
Return 2i+1
Total number of nodes in a Complete Binary Tree
\[t_{\text{Node}}(h)\]
Return 2h-1
The number of terminal nodes (leaf nodes) in a Complete Binary Tree
\[l_{\text{Node}}(h)\]
Return 2h-1
The number of internal nodes (non-leaf nodes) in a Complete Binary Tree
\[i_{\text{Node}}(h)\]
Return 2h-1

Algorithms for: Storing Original Color Space at Leaf Nodes of Tree

**ORIGINAL-HISTOGRAM** (Image, height, width)
Loop x ← 1 to height
Do Loop y ← 1 to width
Do Intensity ← Image [x, y]
Tree [(iNode (h) + 1) + Intensity].count ← Tree [(iNode (h) + 1) + Intensity].count + 1
x ← x + 1
y ← y + 1
Return Tree

Algorithms for: generate quantize color spaces in different level of tree

**LEVEL-HISTOGRAM** (Tree)
Loop x ← iNode (h) + 1 To tNode (h)
Do Lcount ← Tree (x).count
Loop y ← Parent (x) down To 0
Do If x mod 2 ≠ 0
Then Tree [y].intensity ← Tree [x].intensity
Tree [y].count ← Tree [y].count + Lcount
Else If Tree [y].count < Tree [x].count
Then Tree [y].intensity ← Tree [x].intensity
Tree [y].count ← Tree [y].count + Lcount
x ← y
y ← Parent (x)
x ← x + 1

Return Tree

Algorithms to: Calculate the Average Bin Distance

**BIN-DISTANCE** (Tree, h1)
TotBin ← 0
TotBinDist ← 0
Loop x ← iNode (h1) + 2 to tNode (h1)
Do TotBin ← TotBin + 1
TotBinDist ← TotBinDist + (Tree [x].intensity - Tree [x - 1].intensity)
x ← x + 1
AvgBinDist ← TotBinDist / TotBin
Return AvgBinDist
Algorithms for: Calculation of MDT by Identifying the Prominent Bins and Truncate the Non-Prominent Bins.

**CALCULATE-MDT** (Tree, h1)  

Tree [iNode (h1) + 1].prominent $\leftarrow 1$  

TotPrmBin $\leftarrow 0$  

TotPrmBinDist $\leftarrow 0$  

Loop $x \leftarrow$ iNode (h1) + 2 to tNode (h1)  

Do  

If Tree $[x].intensity - Tree [x - 1].intensity \geq$ AvgBinDist  

Then Tree$[x].prominent \leftarrow 1$  

TotPrmBin $\leftarrow$ TotPrmBin + 1  

TotPrmBinDist $\leftarrow$ TotPrmBinDist + (Tree $[x].intensity - Tree [x - 1].intensity)$  

Else Tree$[x].prominent \leftarrow 0$  

$x \leftarrow x + 1$  

MDT $\leftarrow$ TotPrmBinDist / TotPrmBin  

Return MDT

Algorithms for: Redraw the Image Using Truncated Histogram.

**REDRAW-IMAGE** (Image, height, width, Tree, h1, h)  

Loop $x \leftarrow 1$ to height  

Do Loop $y \leftarrow 1$ to width  

Do NewIntensity $\leftarrow$ Image $[x, y] / (tNode (h) / tNode (h1) + 1)$  

If Tree[iNode (h1) + NewIntensity + 1].prominent $\neq 1$  

Then While Tree[iNode (h1) + NewIntensity + 1].prominent $\neq 1$  

Do NewIntensity $\leftarrow$ NewIntensity – 1  

NewImage $[x, y] \leftarrow$ NewIntensity  

$y \leftarrow y + 1$  

$x \leftarrow x + 1$  

Return NewImage

Algorithms for: derive the Horizontal Edge of the image.

**HozEdgeMap** (NewImage, height, width, MDT)  

Loop $x \leftarrow 1$ to height  

Do flag $\leftarrow 1$  

Loop $y \leftarrow 1$ to width  

Do If Flag $= 1$  

Then NewIntensity $\leftarrow$ NewImage $[x, y]$  

NxtNewIntensity $\leftarrow$ NewImage $[x, y]$  

If $|\text{NewIntensity} - \text{NxtNewIntensity}| \geq$ MDT  

Then Flag $\leftarrow 1$  

HozEdgeMapImage $[x, y] \leftarrow$ BLACK  

Else Flag $\leftarrow 0$  

HozEdgeMapImage $[x, y] \leftarrow$ WHITE  

$y \leftarrow y + 1$  

$x \leftarrow x + 1$  

Return HozEdgeMapImage

Algorithms for: derive the Edge of the image.

**EDGEMAP** (HozEdgeMapImage, VerEdgeMapImage, height, width)  

Loop $x \leftarrow 1$ to height  

Do Loop $y \leftarrow 1$ to width
CONCLUSIONS
Medical images obtained from devices such as Ultrasonography, X-Ray, CT and MRI exhibit diverse image characteristics but are essentially collection of intensity variations from which specific abnormalities are needed to be isolated. For edge detection the basic procedure is to identify and trace sharp discontinuities in an image. The discontinuities are meant for sudden changes in pixel intensity which describe boundaries of objects in a scene. Actually edges form the outline of an object. A benefit could be the linking a thing and the backdrop and shows the boundary between overlying objects. Image edge detection also decreases the amount of data and filters out inadequate information, while maintaining the important structural properties in an image. Edge detection is found in various fields like image analysis and pattern recognition. This paper proposes artefact removal algorithm and edge detection algorithm that is equally effective with most medical images.

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