RESEARCH PAPER

FEATURE-BASED EVALUATION OF LOW-DOSE CT IMAGING USING SIFT AND SURF DESCRIPTORS

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ABSTRACT

Human beings give major preference to health. Frequent exposure to radiation doses may eventually lead to the development of cancer. The aim of the project is to reduce the radiation dose while yet maintaining the quality of the image. Restoration techniques, along with investigating image acquisition parameters, help to balance between radiation dosage and image quality. Designing algorithms to investigate the image quality and validating the effects of radiation reduction techniques helps in reducing the dose and improving image quality. In the end, this effort aims to provide improved image quality while minimizing radiation exposure in order to improve diagnostic accuracy and patient safety in CT imaging.

Keywords: Computed tomography; CT imaging; Image quality enhancement; Image enhancement algorithms.

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INTRODUCTION

An essential medical tool for producing finely detailed internal body images is a CT scan. Radiographers or technologists operate CT scanners, which evaluate X-ray interactions with biological tissues using rotating X-ray tubes and detectors. Computer algorithms interpret these measurements to produce cross-sectional images that display the architecture of the body. Patients with pacemakers or implants benefit most from CT scans because they are unable to have an MRI. The physicists Cormack and Hounsfield created this technology in the 1970s, and it has since developed into a versatile imaging method that can be used to image inanimate objects and even aid in medical diagnosis. "Design and Development of Algorithm for Image Quality Enhancement in Computed Tomography" aims to improve medical imaging and patient safety.techniques and improving the parameters of image acquisition. Whereas CT scans enable exhaustive details about the body, it's important to moderate radiation dose with image quality. Research aims to amplify image evaluation and optimize radiation analysis. By investigating various aspects of radiation exposure and image quality, the aim is to provide medical professionals with efficient tools to care for patients. It is a dedication to improve medical imaging and healthcare outcomes, not just a research project. Research tunes the performance of CT scans using a spectrum of image processing algorithms. Gaussian and median filters are used to reduce the unwanted distortions, thereby enhancing the morphological structures in an image. A contrast enhancement model called histogram equalization is used to intensify tissue differentiation in an image reconstruction methods help to improve the quality of the image. These advanced models are integrated to investigate radiation exposure and image quality.

I. LITERATURE REVIEW

The paper titled “Assessment of Radiation Dose and Image Quality of Multidetector Computed Tomography” collected CT images from six hospitals from Jordan. Commercial software was used to conduct statistical analysis of the gathered data. The factors influencing the patients' radiation exposure dose and image quality evaluations were analyzed using averages and standard deviations. Calculations were made for correlations. [1]

Paper titled “Image quality and dose in computed tomography” is where each CT exam was scored as "yes" or "no" based on criteria fulfilment, equally weighted to calculate a quality factor. Patient radiation doses were estimated using Monte Carlo simulation based on computed tomography dose index measurements.[2]

Radiation dosage was evaluated using DPI100, c at the center hole of a CTDI-phantom in the publication "Image quality vs radiation dose of four cone beam computed tomography scanners." An ion chamber calibrated for CT scanners was used to test c for i-CAT and New Ton 3G, DPI100. Image quality evaluated for CBCT and MSCT using an automated method measuring structure thickness and comparing it to actual thickness for accuracy.[3]

The paper titled “Radiation dose and image quality of X-ray volume imaging” is where image noise is the standard deviation of CT density within an ROI in Hounsfield Unit.(HU),,SNR, representing patient body habitus, was determined using image noise and HU. Organ attenuation and noise measurements are used to compute CNR in relation to muscle attenuation..[4]

The paper titled “Enhancement and Smoothing of CT Images for Diagnosis” is where contrast enhancement methods improve visibility in low-contrast images. Their goal is to distinguish objects and enhance information perception. This paper explores popular techniques like Histogram Equalization and Adaptive Histogram Equalization.[5]

The paper titled “Deep learning-based image quality improvement for low-dose computed tomography simulation in radiation therapy” is where they obtained CT scans from 30 patients undergoing frameless brain stereotactic radiosurgery. Using full-dose images, they simulated noisy low-dose projections. Their network, trained on both low and full-dose CTs, produced high-quality images with a 1.6% mean square error at a 0.5% mA reduction. When compared to a sophisticated iterative reconstruction technique, this method significantly improved noise, uniformity, and contrast-to-noise ratio. [6]

In order to evaluate various Cone Beam CT (CBCT) protocols for pediatric dent maxillofacial imaging while addressing radiation risks, the study was published in the paper "Halve the dose while maintaining image quality in pediatric Cone Beam CT." Smaller voxel sizes maintained image quality at reduced exposure levels, achieving a 45% average dose reduction, while larger voxel sizes with lower mA provided unsuitable results. Unsuitable results were obtained with smaller mA voxel sizes. The study confirmed that it is possible to reduce pediatric CBCT dosage significantly without compromising image quality. [7]

The use of deep learning reconstruction imaging in pediatric CT represents a revolutionary advancement in healthcare, according to the publication "Improving image quality and reducing radiation dose for pediatric CT." This innovation uses artificial intelligence to achieve two goals: it reduces radiation exposure and improves image quality, which is a significant step in pediatric healthcare. It could revolutionize the field of pediatric radiology.[8]

In order to improve the extraction of features like SIFT and SURF in scenes with low illumination, an image enhancement technique is introduced in the publication "Analysis of Different Image Enhancement and Feature Extraction Method." It improves scene details by using the Multi-Scale Retinex algorithm, which simulates human vision. Multi-Scale Retinex and SIFT together produce the best dependable feature matches among other enhancement and extraction techniques (MSR, Gamma correction, Histogram Equalization, Sharpening, etc.) according to experimental assessments using a variety of image sets. [9]

A trainable CNN called Lighten Net is suggested for poorly illuminated image enhancement in the publication "A Convolutional Neural Network for Weakly Illuminated Image Enhancement." In order to improve photos with Retinex, it creates an illumination map. It operates better than current techniques, guaranteeing balanced augmentation free from over- or under-amplification. The method includes a novel image synthesis technique for network training and quality assessment.[10]

The paper titled “Image matching method based on improved SURF algorithm” is where the SURF algorithm gained traction for image matching in robotics due to its affine invariance and low computational load. To enhance efficiency, employing a k-d tree and improved BBF algorithms significantly accelerates matching speed, proving simpler and more effective than traditional linear methods, as confirmed by error analysis.[11]

The paper titled “Image processing based detection of lung cancer on CT scan images” is where this paper presents a lung cancer detection method utilizing image processing techniques like Gabor filtering, image segmentation (marker control watershed and region growing), and feature extraction from CT scans. Watershed technique with masking validates improved accuracy and robustness in identifying main features, as investigated in experiments.[12]

A sort of computer method called Paired Cycle-GAN is utilized for image correction in quantitative cone-beam computed tomography, according to the paper titled "Paired cycle-GAN-based image correction for quantitative cone-beam computed tomography." t enhances image quality by transforming images between different domains while maintaining important relationships, improving accuracy in CT scans.[13]

The paper titled “Improvement of megavoltage computed tomography image quality for adaptive helical tomotherapy using cycleGAN-based image synthesis with small datasets” uses CycleGAN, a deep learning technique, improves image quality in helical tomotherapy by synthesizing megavoltage computed tomography images from small datasets. This improves patient care and treatment accuracy by enabling more flexible treatment planning without the need for large amounts of data.[14]

The study, "Parametric Analysis of CT-image-Preprocessing for Improved Performance of Post-Processing Operation," looks at how various CT image preparation techniques affect how well later processing works. It seeks to improve the results of post-processing procedures by optimizing picture preprocessing through the analysis of several parameters.[15]

Bone adaptation parameters, such as mechanostat, derived from live micro-CT scans, vary logarithmically with loading frequency, according to the paper "Mechanostat parameters estimated from time-lapsed in vivo micro-computed tomography data of mechanically driven bone adaptation are logarithmically dependent on loading frequency." This implies that the frequency of stress on the bone may influence the nonlinear impact of mechanical stimuli on bone remodeling.[16]

II. Methodology

Three primary phases are involved in the analysis of radiation levels and X-ray images. First, experiment with several algorithms to enhance the image's quality. Examine and contrast the pictures of high and low dosages. Next, analyze the image quality by measuring particular metrics in both the high and low dosage photos. Next, determine the precise characteristics and specifications of X-ray images with high dosage. Apply enhancement techniques to the low dose photos based on these parameters [17], and then contrast the improved image with high dosage images. Next, measure the image quality using algorithms. Create an algorithm to evaluate the improved image and contrast it with the high-dose image at the end. Compare the high dose photos with these improved low dosage photographs.

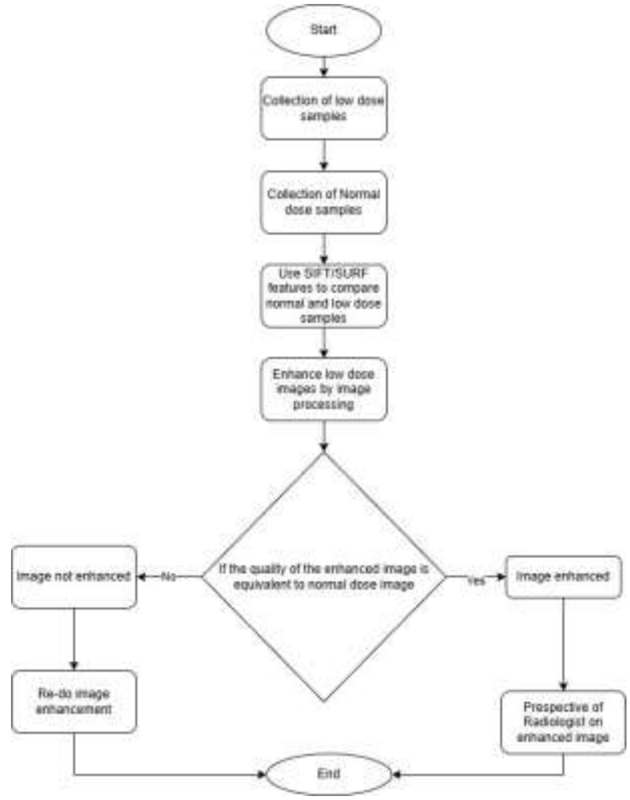

Figure A: Flowchart of Feature-Based Workflow for Low-Dose CT Image Evaluation Using SIFT and SURF

Establishing a solid approach for assessing and improving CT picture quality as well as creating plans to reduce radiation exposure are the goals of image quality evaluation. Determining the sample images is the first step in gathering data to define the imaging parameters. Image quality can be increased by optimizing the CT scan parameters utilizing a variety of enhancing methods and algorithms. In order to minimize radiation exposure [18] to body cells, measures of picture quality and resolution are examined. To determine the relevance of variations in radiation dose and picture quality under various scan conditions, statistical tests are part of data analysis.

Research uses the following models:

• SIFT – Scale Invariant Feature Transform

SIFT technique threads two images merged by detecting SIFT features [19], mapping respective points, assessing a transformation, and aligning two images. It includes:

1. Feature Detection: Use SIFT to detect distinctive characteristics in a pair of images.
2. Feature Matching: Locating similar features in the pictures.
3. Analyzing a transformation between matched points.
4. Image Alignment: Using the predicted transformation, map one image to match the other.
5. Blending: To develop the stitched result, average the aligned images.
6. Visualization: Show the image that has been combined.

• SURF – Speeded Up Robust Feature

SURF is an Image analysis method used in image processing for identification, description, and charecteristics mapping. It can detect and explain specific local characteristics in an image regardless of scale, rotation, or changes in illumination. SURF initially identifies interested spots using a fast Hessian matrix approximation. Then explains these locations using Haar wavelets and intensity details. This method is widely used in tasks like object detection, image stitching, and image registration because of its rate and resistance to different shifts in images. This technique mapped images based on attributes using SURF. During loading and conversion of two images to greyscale, SURF parameters are detected and their descriptors are captured out, the specifications of the two images are collated, and matching points are identified. Finally specific features are viewed by montage visualisation [20] technique.This method aids in

image alignment and object detection, by connecting similar points in an image, based on specific characteristics.

• CNN – Convolution Neural Network

Specific parameters are retrieved by convolution of learnable filters on the input image. Different patterns are identified like edges, textures, or forms. Each of the layers studies a specific filter. Pooling layers are used, ensuring the retaining of vital information. Networks identify images by merging the studied parameters across fully linked layers. To increase internal model parameters (weights and biases) during training, backpropagation is used. To decrease a predefined loss function, these parameters are varied using gradient descent. This helps to visualize the processing system efficiently at computer vision.

• TCA – Target Contrast Adjustment

Pixel intensities vary on x axis (grayscale images: 0 to 255) and y axis (frequency of each intensity). MATLAB histogram function is used to analyze frequency distribution of pixel intensities. Program is written in such a way that it reads the image, converts it to greyscale and then use the `imhist function. These techniques help in image analysis and thereby improving the image quality wrt contrast, brightness and pixel value distribution.

• Histogram Equalization

MATLAB histogram function is used to display the frequency distribution of pixel intensities in an image. The `imhist` or `histogram` functions are passed on to the code to produce a histogram after the image is read and if necessary, convert it to greyscale. The incidence of pixel intensities, which are normally shown on the x-axis and range from 0 to 255 for greyscale images, and the frequency of each intensity on the y-axis are both illustrated in the histogram. This model is important for image analysis and enhancement in numerous image processing applications, as it helps to understand the contrast, brightness, and distribution of pixel values.

• Denoised image (non-local image)

The technique of removing noise in an image by comparing and averaging identical patches from the entire image in lieu of comparing pixels side by side is attributed to as non-local. Technique involves identifying patches with indentical structures and averaging them, which minimises noise and preserves details in an image. It is an efficient way of minimising noise without blurring vital characteristics of images. [21]

• Denoised image (Gaussian filter)

A Gaussian filter blurs an image and reduces noise by using a mathematical procedure that mean the pixel values within a specified region. The filter smoothes the image while preserving its overall structure, by allocating weights to adjacent pixels according to a Gaussian distribution.

• Harries Corner Detection

This is one of the most complicated models and is used by different image processing applications which requires the detection of significant corners or features of an image. Corners can be detected by extracting significant details like shapes, patterns, boundaries of objects within the CT scan. This helps for further accurate segmentation, registration, and analysis of medical images, which can help in diagnosis and treatment. It also enhances the image quality, resulting in more accurate imaging results. Embedding this with CT image processing algorithms can remarkably enhance the efficiency and productivity of medical imaging procedures, which can finally benefit patients.

• Sobel Operator

Augmentation of CT images employing only operators is one of the advanced techniques in medical imaging. To identify specific details, edges, or textures in the CT image, operators such as gradient, Laplacian, or Sobel operators are used. The technique is useful in focusing the attention of the viewer on minute details that may be of significant importance in the analysis or diagnosis of the CT image. The use of operators in the augmentation of CT images is useful in enhancing the interpretability and diagnostic capabilities of the images by emphasizing specific features or anomalies. Furthermore, the technique of operator-based augmentation can be useful in research aimed at understanding complex medical issues.

• Canny Edge Detector

A very effective method for analyzing and enhancing medical images is CT image processing using the Canny edge detector. The Canny edge detector is no stranger to the world of image processing, as it is known for its accuracy in detecting the boundaries and edges of a particular image, as well as its effectiveness in eliminating noise and false positives. Medical professionals can effectively and efficiently isolate medical images and anomalies from CT scans using this method. The images produced by the Canny edge detector are very effective in helping radiologists and medical professionals diagnose issues and plan treatments by providing them with a clear view of the most important aspects of the image. In addition, the Canny edge detector can be used in automated image analysis systems, allowing for the objective analysis of very large data sets in a very short period of time. Its versatility and reliability improve patient care and advances in medical research.

• Laplacian of Gaussian

The Laplacian of Gaussian (LoG) is an advanced technique used in the CT image processing that improves the quality and interpretability of medical images. The LoG algorithm applies the Laplacian operator in conjunction with the Gaussian smoothing filter to detect and highlight edges and fine details in the CT images. Initially the image is processed with a Gaussian filter, which is very efficient in removing noise while preserving essential information. To highlight edges and fine details for better visibility to the human eye, Laplacian operator is then applied. Outcome of this operation enables the medical professionals to easily distinguish anatomical details, lesions, and abnormalities in the CT images. It also accurately detects edges, which assists in the accurate separation and analysis of medical information. Application of this technique includes organ segmentation, tumor detection, and treatment planning.

• Affine Transformation

Affine Transformations are pivotal for tasks such as image registration, where it is vital to register images from different sources. Images are resized, rotated, sheared, and translated using this technology. It also yields tools for aligning images, correcting distortions, and combining information from multiple sources, all of which will boost the outcome of medical diagnosis and treatment. It provides 3D reconstruction from 2D images, which is vital in surgical navigation and planning. In addition, they allow for the combination of information from multiple sources, such as CT scans and MRI scans, which are important in improving diagnostic accuracy.

• Thresholding

Thresholding is an approach used for the separation of regions of interest or objects from the background of an image. This is done by setting a threshold level, below which pixels are categorised as background and above which pixels are grouped as object pixels [22]. A few traits, like cancer or bones, are highlighted using this strategy, which makes analysis and diagnosis easier.

There are different methods of applying the thresholding technique, like adaptive thresholding, where diverse threshold levels are seasoned for different parts of the image, or global thresholding, where a single threshold level is habituated for the entire image. In addition, Otsu's approach can automatically assess the optimal threshold level using the histogram of the image.

• K mean clustering

K-means clustering is a technique that forms clusters of analogous pixels. Pixels are repeatedly allocated to the nearest cluster center, and the cluster centers are then adapted based on the mean pixel value per cluster. By splitting down images into different regions based on pixel intensity or other criteria, this technique helps in the finding of structures or abnormalities in medical images, such as tumors or organs. Applications include image segmentation, where this technique helps to identify regions of interest, aiding in research, diagnosis, and treatment.

• Watershed segmentation

The technique used in medical image processing for the division of items or regions of interest in an image is called "watershed segmentation." It works by considering the image as if it were a topographic surface, where peaks are denoted by pixels with increased intensity values and valleys are represented by pixels with lower intensity values. The regions of interest are highlighted in the image using markers [23]. By flooding the image with the markers, the software creates basins that denote different regions or objects. Finally, the segmentation process is completed by identifying the boundaries of these basins. This technique is applied during segmentation of overlapping or irregularly shaped objects in medical imaging, such as tumors or blood vessels.

• Erosion and dilation

Erosion and dilation are critical operations that are applied to improve and modify images for various diagnostic and analytical tasks. Through the removal of pixels along the edges of objects in an image based on a defined structural element, erosion reduces or thins out the boundaries of the objects. This makes it easier to identify distinct features through the segmentation and separation of overlapping structures, such as tissues and organs. Conversely, dilation expands the boundaries of an object by adding pixels to it based on the structuring element. This operation helps to smooth out irregularities in the image, repair damaged structures, and fill gaps. Erosion and dilation are often used in medical applications to enhance the accuracy of diagnosis and treatment plans in operations such as image segmentation, feature extraction, and noise removal. These operations are critical to various medical imaging techniques, such as MRIs, CT scans, ultrasounds, and microscopes, and help medical professionals interpret images more accurately and reliably.

• Opening and closing

Opening and closing are very important morphological procedures in medical image processing that enhance and analyze images, particularly in object detection, image segmentation, and noise removal.

Erosion and dilatation are the two processes involved in opening. Erosion is a process that removes noise and details in the image by smoothing the edges of the image and removing small structures. The remaining structures are then enlarged by the process of dilation, retaining their overall shape and regaining the essential features.

On the contrary, the closing process undoes the above operation. The process involves dilation followed by erosion. Dilation expands the boundaries of an object, helping to fill small gaps between nearby structures. This is followed by erosion, which removes unwanted protrusions and restores the objects to their original size and shape.[24].

• Skeletonization

In medical image processing, skeletonization is an important technique for emphasizing and analyzing the essential structural information of biological structures. It involves simplifying complex structures like blood vessels, bones, or nerves into simple models called skeletons.

This process involves the gradual removal of unnecessary pixels along the boundaries of the structures until only a one-pixel-wide skeleton is obtained. This skeleton is very useful in a variety of medical applications like vascular structure analysis, neuronal path tracking, and bone structure analysis, since it preserves the connectivity and topological information of the original structures. Skeletonization allows for the effective analysis, visualization, and understanding of medical images by simplifying complex anatomical information to its most basic elements [25]. It provides medical practitioners with essential information about the structures and their interactions in the human body, which is useful in tasks such as disease diagnosis, surgery, and treatment analysis.

• HOG - Histogram Of Oriented Gradient

In medical image processing, the Histogram of Oriented Gradients (HOG) feature descriptor method is commonly employed to detect objects or patterns within images. This method determines the gradient orientation distribution for particular regions of the image.

Gradients, or intensity variations, are determined for each of the image's small cells. The primary directions of the gradient variations are then described using a histogram of gradient orientations, which is calculated for each cell.

The histograms are normalized to reduce the effects of contrast and lighting variations. The final feature vector, which can be used for object detection or classification in medical images, is obtained by combining the histograms of neighboring cells. Due to its ability to extract important texture and shape information, HOG is employed in medical imaging for applications such as organ segmentation and tumor detection.

III. RESULTS AND DISCUSSION

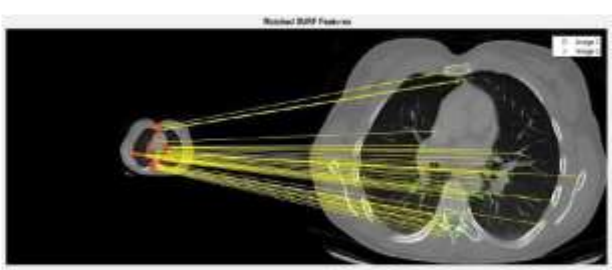

Fig 1: Image comparison using the SURF algorithm, with a focus on keypoint matching and robustness evaluation.

The comparison of two photographs with the same coordinates is described in Figure 1. In the comparison of the SURF (Speeded Up Robust Features) method, the performance of the method is measured using factors such as robustness to image changes, speed, and robustness of feature detection. In the evaluation of algorithmic strengths and weaknesses, the evaluation typically involves testing on datasets of different sizes, rotations, and lighting conditions. . In order to assist in the selection of the most appropriate method for specific image processing tasks, such as object recognition and image registration, the comparison aims to identify which method is [1] superior in terms of speed, accuracy, and robustness.

Fig 2:(a) Revised dental x-ray picture (b) Original dental x-ray image

The enhanced image from the noisy image is shown in Figure 2. Histogram Equalization, a method that aims to enhance the contrast of an image by redistributing the pixel values over a larger range, is utilized by the code to enhance images. An image is loaded, converted to grayscale, and histogram equalization ('histeq') is performed to enhance contrast. The original and enhanced images are then displayed side by side. The method aims to improve the contrast of the image by spreading the histogram over a larger range.

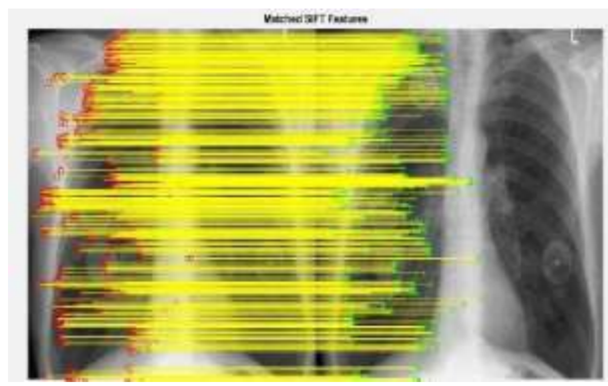

Fig. 3. Keypoint detection and feature matching using SIFT..

The SIFT algorithm, which calculates the keypoint descriptors from images through the "extractFeatures" function, then calculates the matches of these descriptors through the "matchFeatures" function, and finally uses geometric verification, such as RANSAC's "estimateGeometricTransform," to eliminate incorrect matches, is employed for image comparison in Figure 3. Through the consideration of invariant properties, scale, rotation, and translation variations, this algorithm is able to identify similar keypoints in images, which is a very important step in object recognition or image registration.

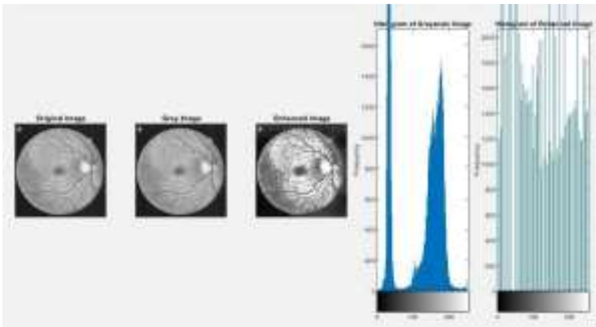

Fig 4: (a) The original image; (b) The greyscale version; (c) The enhanced image; (d) The greyscale image's histogram; and (e) The histogram of the histogram-equalized image.

The histogram equalization process for the given image is illustrated in Figure 4. To apply the Histogram Equalization technique, the image needs to be read and converted to a grayscale image. The 'histeq' function is used, which determines the histogram of the grayscale image and rearranges the pixel values of the image to get a more evenly distributed histogram. This helps in improving the contrast of the image by making it easier to distinguish between the darker and lighter regions. Because the stretching of the histogram successfully modifies pixel intensities to encompass a larger range, improving overall contrast, the resultant image exhibits increased visual quality.

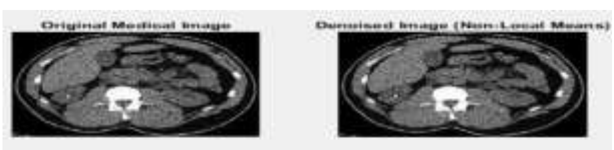

Fig 5. (a) Original Image, (b) Image denoised using the Non-Local Means (NLM) filter.

As seen in Figure 5, denoising in non-local image processing uses redundancy in picture structures to enhance noisy parts of an image by employing similar patches from the image. It provides a reliable method of noise removal while maintaining significant image features by restoring clean details through matching patches throughout the image.

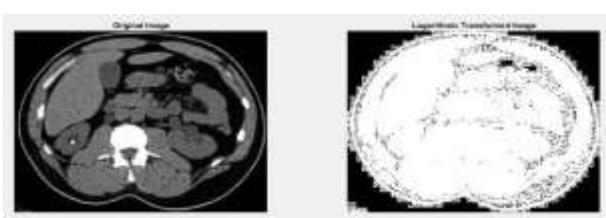

Fig 6. (a) Original Image, (b) Image after logarithmic transformation.

The logarithmic transformed image theory, as seen in Figure 6, modifies picture pixel values by applying logarithmic functions. It improves visibility in both bright and dark areas and raises the overall quality of the image by condensing a large range of values into a smaller scale. Details that could normally be hidden are made visible by this alteration.

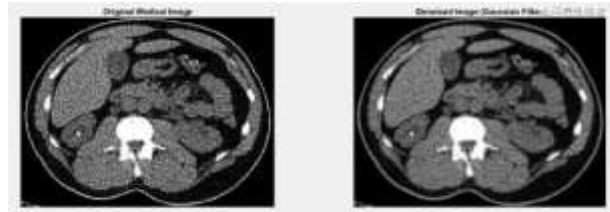

Fig 7. (a) Original Image, (b) image denoised using a Gaussian filter.

Figure 7 illustrates how a number of things might cause noise in the photos. Gaussian denoising emphasizes nearby values by substituting a weighted average of the neighboring pixels for each pixel's value. This improves the image's clarity by lowering high-frequency noise and smoothing the edges without noticeably blurring them.

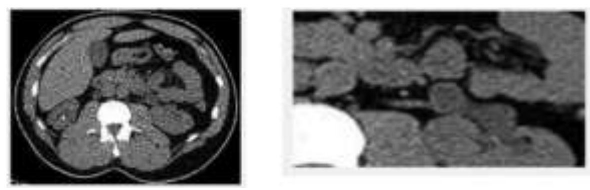

Fig. 8. (a) Original Image, (b) Zoomed-in region of the low-dose image.

A low-dose image's zoomed-in perspective, as seen in Figure 8, exposes little features because of the image's lower exposure. In this case, fewer X-rays reach the detector, resulting in a less clear and grainy image. In medical imaging, it is necessary to strike a balance between image quality and safety because increasing the dose can improve details but may also increase radiation exposure.

Fig. 9. (a) Original image, (b) brightened image, and (c) contrast-enhanced image.

Figure 9 illustrates how an image's clarity and visual attractiveness are influenced by its brightness and contrast. Contrast and brightness are the two faces of the coin, which are used in image quality enhancement. Details and depth of the image's details depend on the perception of the image. The difference between the light and dark regions is defined as contrast. Brightness describes the general lightness or darkness.

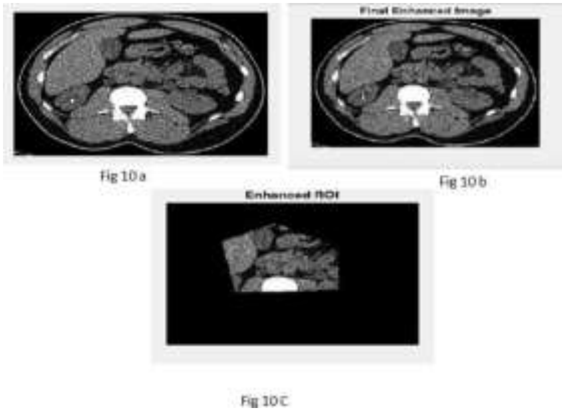

Fig. 10. (a) The original image, (b) The final enhanced image, and (c) The enhanced image's ROI.

Figure 10 focuses on the Region of Interest (ROI) of the enhanced image. A region of interest is a part of the original image, which is used for further work. Instead of focusing on the entire image, one can focus on a particular area of the image. This improves efficiency in object recognition and feature extraction.

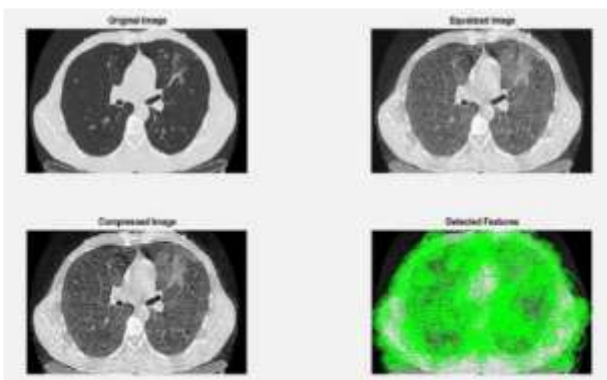

Fig. 11. (a) Original image, (b) image-equalized, (c) image-compressed, and (d) feature-detected image.

Figure 11 shows an example of a CT scan of a lung structure. A CT scan aids in clear visualization of the lungs. Equalized images enhance contrast, compressed images conserve storage space, and surface detection helps in the identification of anomalies. Surface detection identifies cancerous growths or nodules. Compressed images conserve features while minimizing file size. Equalized images improve visualization by maximizing contrast.

Fig. 12. (a) Original image, (b)Image - sharpened, and (c) Image - smoothed.

Figure 12 shows the sharpened and smoothened lung image. A sharpened image improves contrast for edges within a lung CT outcome. Smoothened images decrease noise by removing minute details and pixelation. Both the techniques aim for perfect diagnosis and further treatment.

Fig. 13. Result of Harris corner detection (end result)

Figure 13 shows the implementation of Harris corner detection in CT lung images. Crucial points are noted where intensity variations occur. Junctions are located using these points. Artifacts such as lesions or nodules can be identified for a lung image. Thus increasing the efficiency of diagnosis of lung disease.

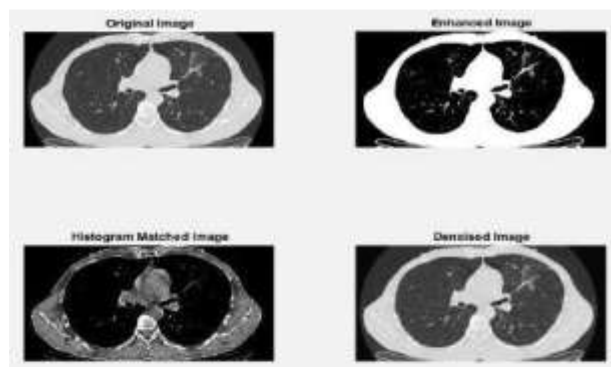

Fig. 14. (a) Original image, (b) Enhanced image, (c) Histogram-matched image, and (d) Denoised image.

Figure 14 shows enhanced images in CT lung. Contrast and brightness are adjusted to easily identify the lung features. Smoother and clearer images are observed after removing noise in the images. (Example: graininess). Histogram matching helps in matching the intensity distribution of pixels with a reference image. By using this technique, consistency increases, thus enhancing the quality of the image. When the two techniques are combined, they enhance CT scans for better diagnosis of pulmonary diseases.

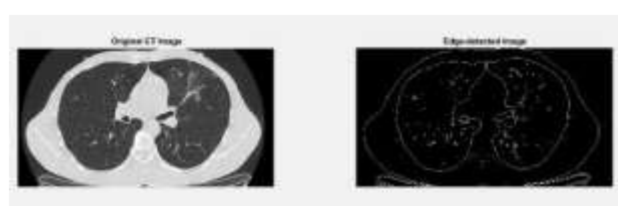

Fig. 15. (a) Original CT image and (b) Edge-detected image.

As seen in Figure 15, edge detection in CT lung images helps identify structural features such as blood veins, airways, and anomalies by highlighting the borders between various tissues. Edge detection enables doctors to analyze the spatial relationships between the lung anatomy and enhances the visibility of small details by emphasizing the variation in pixel intensity. This helps in the accurate diagnosis and treatment of respiratory diseases.

Fig. 16. (a) Original image (b) Sobel operator result, (c) Canny edge detector result, and (d) Laplacian of Gaussian result.

Through gradient magnitude calculation, the Sobel operator in CT lung images increases the contrast between tissues and edges (Figure 16). The Canny edge detection operator further refines the edges by removing noise. The Laplacian of Gaussian operator combines edge detection and smoothing to detect edges at different scales. When combined, these methods improve lung structure visibility and help diagnose respiratory diseases.

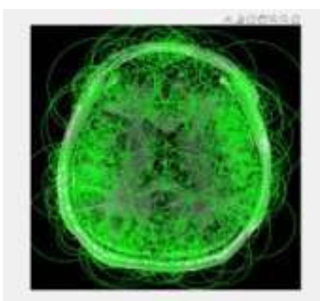

Fig. 17. Results of feature extraction.

Figure 17 illustrates how feature extraction in CT brain scans identifies important features, such as shapes, textures, and patterns. By emphasizing anomalies such as tumors, lesions, or hemorrhages, these characteristics help in the diagnosis of neurological disorders. Healthcare practitioners can make more educated decisions about patient care and treatment plans by deriving pertinent information from the pictures and better understanding the structural alterations in the brain.

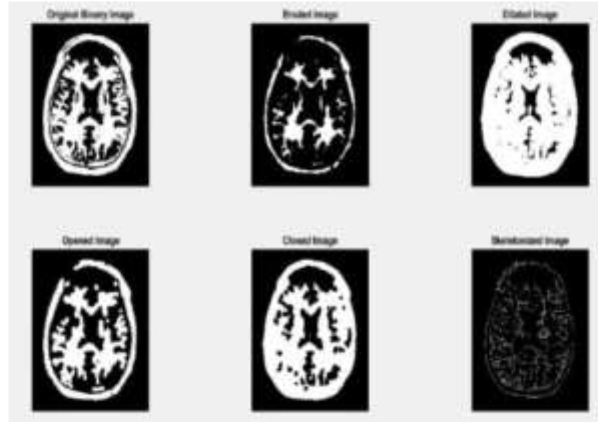

Fig. 18. (a) Original binary image, (b) Eroded image, (c) Dilated image, (d) Opened image, (e) Closed image, and (f) Skeletonized image.

Figure 18 illustrates how contrast and brightness adjustments in CT brain outputs increase the visibility of brain structures. Dilation increases the prominence of recognized features by enlarging them. Feature extraction is aided by opening and closing processes, which smooth and refine borders, respectively. By reducing structures to their most basic outlines or routes, skeletonization makes it easier to do additional analysis and interpretation. These methods enhance CT brain pictures for precise neurological disease diagnosis and therapy planning.

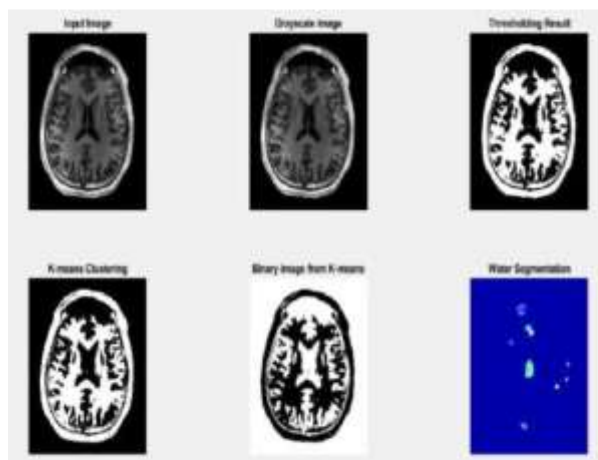

Fig. 19. Stages of image segmentation: (a) Input image; (b) grayscale conversion; (c) thresholding; (d) K-means clustering; (e) binary image derived from K-means clustering; (f) final watershed segmentation result.

Grayscale CT brain scans of the brain with different intensities are shown in Figure 19. By establishing intensity thresholds, thresholding divides the vision into areas of the brain and eliminates background noise. K-means clustering improves tissue distinction by assembling images into clusters according to similarity. The diagnosis and treatment of neurological disorders are aided by binary pictures using k-means clustering, which reduce the image to black and white and emphasize certain areas for additional examination.

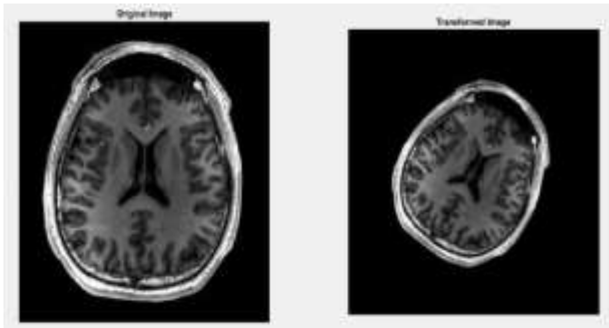

Fig. 20. (a) Original image; (b) image after affine transformation..

As seen in Figure 20, converted CT brain scans are subjected to geometric adjustments such as translation, scaling, or rotation in order to align or correct the image spatially. By resizing photos for standardized analysis, correcting orientation issues, or aligning images with other medical data, these changes increase the precision of neurological disorder diagnosis and treatment planning.

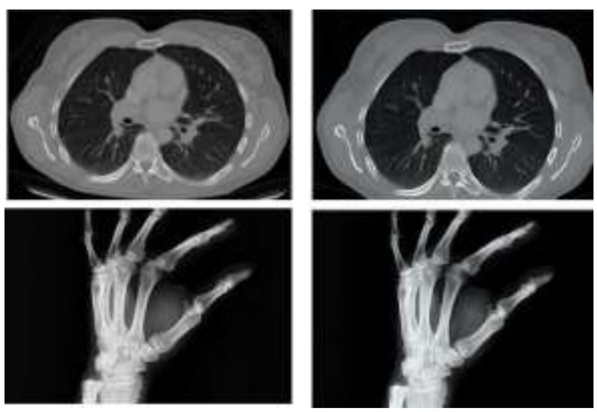

Fig. 21.(a) Low-dose images; (b) enhanced images generated using ESRGAN.

The ESR-GAN, or Enhanced Super-Resolution Generative Adversarial Network, is a state-of-the-art deep learning model designed especially for picture super-resolution tasks (Figure 21). The approach uses a dual-generator architecture, with one refinement network to further improve the output and another generator network to produce high-resolution images. ESR-GAN continuously produces high-quality images with improved details and textures by utilizing perceptual loss functions and adversarial training procedures, guaranteeing visually appealing outcomes. These techniques are widely used in satellite imaging and medical imaging, enhancing the low resolution images. Effective implementation of realistic transformations of pictures and complex properties of image aids in real time applications.

IV. Conclusion

A novel algorithm was developed which increases the quality of the image by reducing the noise in the image. Finally the algorithm, which has the ability to enhance contrast, reduce noise artifacts, and increase the sharpness of images, has great potential to impact the radiologists and medical practitioners with sharper and more accurate images. Outcomes of the new algorithm include clear image, good resolution, thus improving the overall quality of the image. Moreover, the algorithm has been tested on a large number of computed tomography scan datasets, showing its efficiency. Because of its efficiency, the algorithm can be applied in real-time image enhancement, which increases the speed of decision-making. The project gains its implications in the medical domain. It helps the clinicians and doctor to predict and identify the issues with the help of a clear image. Thus improving the diagnostic imaging accuracy and reducing the need for additional imaging tests with the more user-friendly interface. As a future scope, radiation dose can be reduced by optimizing the image quality. Automatic exposure control techniques can be implemented. Any specific case by case study of a particular organ can be analyzed and compared with the existing techniques.

References

[1] H. Al-Ewaidat, X. Zheng, Y. Khader, M. Abdelrahman, M. K. M. Alhasan, M. A. Rawashdeh, and D. S. Al Mousa, "Assessment of radiation dose and image quality of multidetector computed tomography," *Radiation Physics and Chemistry*, vol. 151, pp. 22–29, 2018, doi: 10.1016/j.radphyschem.2018.05.012.

[2] A. G. Jurik, K. A. Jessen, and J. Hansen, "Image quality and dose in computed tomography," *European Radiology*, vol. 26, no. 11, pp. 3838–3845, Nov. 2016, doi: 10.1007/s00330-016-4276-1.

[3] M. Loubele, R. Jacobs, F. Maes, K. Denis, S. White, W. Coudyzer, I. Lambrichts, D. Van Steenberghe, and P. Suetens, "Image quality vs radiation dose of four cone beam computed tomography scanners," *Dentomaxillofacial Radiology*, vol. 46, no. 2, 2017, Art. no. 20160274, doi: 10.1259/dmfr.20160274.

[4] J. Paul, V. Jacobi, M. Farhang, B. Bazrafshan, T. J. Vogl, and E. C. Mbalisike, "Radiation dose and image quality of X-ray volume imaging systems," *European Journal of Radiology*, vol. 113, pp. 94–101, 2019, doi: 10.1016/j.ejrad.2019.02.008.

[5] Malik S. H., Lone T. A., and Quadri S. M. K., "Contrast enhancement and smoothing of CT images for diagnosis," Proc. 2nd Int. Conf. Computing for

Sustainable Global Development (INDIACom), New Delhi, India, Mar. 2015, pp. 2214–2219.

[6] Tonghe Wang, Yang Lei, Zhen Tian, Xue Dong, Yingzi Liu, Xiaojun Jiang, Walter J. Curran, Tian Liu, Hui Kuo Shu, and Xiaofeng Yang "Deep learning-based image quality improvement for low-dose computed tomography simulation in radiation therapy," Journal of Medical Imaging 6(4), 043504, 24 October 2019.

[7] A. C. Oenning, R. Pauwels, A. Stratis, K. De Faria Vasconcelos, E. Tijskens, A. De Grauwe, R. Jacobs, B. Salmon, *et al.*, "Halve the dose while maintaining image quality in paediatric Cone Beam CT," *Scientific Reports*, vol. 9, Art. no. 5521, Apr. 2019, doi: 10.1038/s41598-019-41949-w.

[8] S. L. Brady, A. T. Trout, E. Somasundaram, C. G. Anton, Y. Li, and J. R. Dillman, "Improving image quality and reducing radiation dose for pediatric CT by using deep learning reconstruction," *Radiology: Artificial Intelligence*, vol. 2, no. 3, May 2020, Art. no. e190082, doi: 10.1148/ryai.2020190082.

[9] L. V. Lozano-Vázquez, J. Miura, A. J. Rosales-Silva, A. Luviano-Juárez, and D. Mújica-Vargas, "Analysis of different image enhancement and feature extraction methods," *IEEE Access*, vol. 10, pp. 102345–102357, 2022..

[10] C. Li, J. Guo, F. Porikli, and Y. Pang, "A convolutional neural network for weakly illuminated image enhancement," *IEEE Trans. Image Process.*, vol. 28, no. 10, pp. 4786–4797, Oct. 2019, doi: 10.1109/TIP.2019.2910426.

[11] X. Jia, X. Wang, and Z. Dong, "Image matching method based on improved SURF algorithm," in *Proc. Int. Conf. Image, Vision and Computing (ICIVC)*, Chongqing, China, 2018, pp. 225–229, doi: 10.1109/ICIVC.2018.8492786.

[12] B. Abdillah, A. Bustamam, and D. Sarwinda, "Image processing-based detection of lung cancer on CT scan images," in *Proc. Int. Conf. Computer Science and Computational Intelligence (ICCSCI)*, Yogyakarta, Indonesia, 2019, pp. 540–545, doi: 10.1109/ICCSCI.2019.8887482.

[13] J. Harms, Y. Lei, T. Wang, R. Zhang, J. Zhou, X. Tang, W. J. Curran, T. Liu, and X. Yang, "Paired cycle-GAN-based image correction for quantitative cone-beam computed tomography," *Medical Physics*, vol. 46, no. 9, pp. 3998–4009, Jun. 2019, doi: 10.1002/mp.13656.

[14] Y. Lei, Y. Fu, T. Wang, X. Liu, H. Mao, W. J. Curran, T. Liu, and X. Yang, "Improvement of megavoltage computed tomography image quality for adaptive helical tomotherapy using cycleGAN-based image synthesis with small datasets," *Medical Physics*, vol. 46, no. 12, pp. 5317–5329, Dec. 2019, doi: 10.1002/mp.13870.

[15] M. B. Shankar, S. K. Satapathy, and A. K. Ray, "Parametric analysis of CT-image preprocessing for improved performance of post-processing operation," in Proc. Int. Conf. Advances in Computing, Communications and Informatics (ICACCI), Mysuru, India, Sep. 2015, pp. 2137–2142, doi: 10.1109/ICACCI.2015.7275956.

[16] F. Schulte, R. Ruffoni, M. Christen, and R. Müller, "Mechanostat parameters estimated from time-lapsed in vivo micro-computed tomography data of mechanically driven bone adaptation are logarithmically dependent on loading frequency," Bone, vol. 56, no. 2, pp. 417–423, Oct. 2013, doi: 10.1016/j.bone.2013.07.020.

[17] W. Lee, F. Wagner, A. Galdran, Y. Shi, W. Xia, G. Wang, X. Mou, and et al., *"Low-dose computed tomography perceptual image quality assessment," Med. Image Anal.*, vol. 99, Jan. 2025, Art. no. 103343, doi: 10.1016/j.media.2024.103343.

[18] F. Zhang, Y. Liu, and X. Zhang, *"Low-dose CT image quality evaluation method based on radiomics and deep residual network with attention mechanism," Expert Syst. Appl.*, vol. 238, 15 Mar. 2024, Art. no. 122268, doi: 10.1016/j.eswa.2023.122268.

[19] R. Rani, S. K. Grewal, and K. Panwar, "Object recognition: Performance evaluation using SIFT and SURF," Int. J. Comput. Appl., vol. 75, no. 3, pp. 39–47, Aug. 2013, doi: 10.5120/13094-0375

[20] Ş. Işık and K. Özkan, "A comparative evaluation of well-known feature detectors and descriptors," *Int. J. Appl. Methods Electron. Comput.*, doi: 10.18100/ijamec.60004.

[21] Y. Bakhshi, S. Kaur, and P. Verma, "Face recognition using SIFT, SURF and PCA for invariant faces," *Int. J. Eng. Trends Technol.*, vol. 34, no. 1, pp. 39–42, 2016, doi: 10.14445/22315381/IJETT-V34P208.

[22] K. B. R., R. G., and P. G., "Performance comparison of various feature descriptors in object category detection application using SVM classifier," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 5, Mar. 2019.

[23] M. Bansal, M. Kumar, and M. Kumar, "2D object recognition: a comparative analysis of SIFT, SURF and ORB feature descriptors," *Multimedia Tools Appl.*, vol. 80, pp. 18839–18857, 2021, doi: 10.1007/s11042-021-10646-0.

[24] L. Liu, "Model-based Iterative Reconstruction: A Promising Algorithm for Today's Computed Tomography Imaging," *J. Med. Imaging Radiat. Sci.*, vol. 45, no. 2, pp. 131–136, Jun. 2014

[25] H. H. Muhammed, "Optimization of Radiation Doses in Panoramic X-Ray Examination using Automated Image Processing", IEEE conference on imaging, systems and techniques, Vol. 2, No. 3, pp. 361-364, 2014. DOI: 10.1109/IST.2014.6958505