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CHEST X-RAY IMAGE DENOISING FOR COVID-19 APPLICATIONS

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ABSTRACT

In medical imaging systems, denoising is one of the important image processing tasks. Automatic noise removal will improve the quality of diagnosis and requires careful treatment of obtained imagery. Computed tomography (CT) and X-Ray imaging systems use the X radiation to capture images and they are usually corrupted by noise following a Poisson distribution. Due to the importance of Poisson noise removal in medical imaging, there are many state-of-the-art methods that have been studied in the image processing literature. These include methods that are based on total variation regularization, wavelets, principal component analysis etc.

In this work, a non-local means with packing of multiple patches (NLM-PMP) model is adopted for denoising of chest x-ray images. The integration of several high-quality denoising methods in image processing software for medical imaging systems will be always excellent option and help further image analysis for computer-aided diagnosis.

Keywords: Chest X-ray, Computed tomography (CT), Covid-19.

1. INTRODUCTION

In medical imaging,1,2 different modalities such as X-RAY, single photon emission tomography (SPECT), computer tomography (CT), and magnetic resonance imaging (MRI) are used to capture complementary information. For example, as shown in Figure 1, CT image (left-hand side) provides hard tissue information such as bone structure, whereas MRI image (right-hand side) provides soft substance information such as flesh. However, a radiologist needs both CT and MRI information in a single image for better diagnosis and treatment. Hence, useful or complementary information from different sensing technologies has to be integrated into an image. Image fusion is a process of combining useful and complementary information of source images into a single image. This fused image is helpful in computer assisted surgery and radio surgery. In this article, we concentrated on fusion of CT and MRI images of "human brain." Fusion process can be performed at three levels. They are pixel or signal level, objective or feature level and symbolic or decision level. In pixel-level image fusion, the process of fusion is performed on information present in the co registered input imagery pixel by pixel. Contribution in this area can be found in Refs. 3–5. In objective level image fusion, property descriptors, features, and object labels derived from each source image are used for fusion.6 Symbolic level image fusion is a high-level fusion. Here, local decision makers are derived from objective level fusion results. Finally, fusion is employed on probabilistic decision information extracted from these decision makers.7 This article focuses on pixel-level fusion

Depending on the principle of imaging equipment, medical images can be divided into anatomical images and functional images. Because of the different imaging principle, they have different advantages. If these two kinds of image information integrate as a basis for medical diagnosis, clinicians will make more rapid and more accurate medical result. X-RAY and CT fusion on the same machine is a typical representative of the multimodal medical image fusion technology. One image can get X-RAY and the corresponding parts of CT. It combines the advantages of both and provides a reliable basis for diagnosis. X-RAY/CT image fusion has become a research hotspot at present. There are many multimodal medical image fusion methods. Because of the good sub-frequency features in the transform domain, the wavelet transform has been widely used. Multiwavelet is an extension from wavelet theory and has several advantages in comparison with scalar wavelets on image processing. It can simultaneously possess many desired properties such as short support, orthogonality, symmetry, and smoothness. These properties are very important for the image analysis and processing. This paper studies the basic principles of multiwavelet transform and characteristics of multiwavelet coefficients and designs a medical image fusion algorithm based on multiwavelet transform for the X-RAY/CT image fusion. Experimental results show that fusion image. Combines information of the source images, adds more details and texture information, and achieves a good fusion result

A computed tomography (CT) scan, also called a CAT scan, uses x-rays to take pictures of the head from many different angles. The pictures provide a detailed, cross-sectional view of specific areas of the brain. CT scans are widely used and less expensive than other scanning technologies. A CT scan shows changes in bone better than any other imaging method. It is also the only scanning technique that shows images of bone, blood vessels etc. at the same time. A CT scan is often used in emergency rooms because it can be performed quickly to screen people who have had some type of trauma, a stroke or other life-threatening condition. CT scans are used to help diagnose many medical conditions including strokes, head trauma, tumors, hydrocephalus, blood clots, cerebral atrophy, internal bleeding, skull fractures, brain aneurysms, and hearing loss. CT scans are not used to diagnose Alzheimer’s disease. They are used to confirm or rule out other causes of dementia in people who show signs of memory loss.

A X-RAY image helps to diagnose various diseases such as brain tumors or torn ligaments. X-RAY scan is a test that provides very clear pictures of structures inside the body. X-RAY image provides clear soft tissues information but no bones information. That is to say, the same object in the two medical images appears very distinctly. Hence, in order to support more accurate information for diagnosis and treatment it is necessary to fuse them by using their complementary information.

2. RELATED WORK

2.1 In "Image Fusion Based On Wavelet Transforms"

In this paper, we have presented image fusion based on wavelet transform. Medical Image Fusion is a sort of data fusion and developed from that into a new data fusion technology. The aim of fusion is the combination of images to integrate the information of each individual technique and reduce the uncertainty of the image information. Computed tomography (CT), and positron emission tomography (X-RAY) provide data conditioned by the different technical, anatomical and functional properties of the organ or tissue being studied, with values of sensitivity, specificity and diagnostic accuracy variations between them Many methods exist to perform image fusion. The very basic ones are the Probabilistic Approximation model. The wavelet approach gives better accuracy and increased information compared to the previous techniques

2.2 In "Image Fusion Algorithm Based on Wavelet Transform and IDFC Transform.

"Image fusion is the method of combining relevant information from two or more images into a single image. The resulting final image will be more informative than any of the input images. The discrete wavelet transform has become a very useful tool for fusion. Some other fusion methods are also there, such as Lapacian pyramid based, curve let transform based etc. These methods show a best performance in spatial and spectral quality of the fused image compared to other spatial methods of fusion. Wavelet Transform has good time-frequency characteristics. Its excellent characteristic in one-dimension can't be extended to two dimensions or multi-dimension simply. Separable wavelet which was spanning by one-dimensional wavelet has limited directivity. This paper introduces the Second Generation Curve let Transform and uses it to fuse images, different kinds of fusion methods are compared at last. The experiments show that the method could extract useful information from source images to fused images so that clear images are obtained Image fusion is emerging as a vital technology in many military, surveillance and medical applications. It is a sub area of the more general topic of data fusion, dealing with image and video data. The capacity to combine complementary information from a range of distributed sensors with different modalities can be used to provide enhanced performance for visualization, detection or classification tasks. . Image fusion methods can be broadly divided into two - spatial domain fusion and transform domain fusion. The image fusion methods such as averaging, Brovey method, principal component analysis (PCA) and IHS based methods fall under spatial domain approaches. Another important spatial domain image fusion method is the high pass filtering based technique. Here the high frequency details are inserted into up sampled version of MS images. The disadvantage of spatial domain approaches is that they give us spatial distortion in the fused image. Spectral distortion becomes a negative factor while we go for further processing that can be very well handled by transform domain approaches on image fusion. The multi-resolution analysis has become a very useful tool for analyzing remote sensing images[1]. Multi-sensor data often present opposite information about the scene or object of interest, and thus image fusion provides an effective method for comparison and analysis of such data. There are several advantages of multi-sensor image fusion: wider spatial and temporal coverage, extended range of operation, decreased uncertainty, improved reliability and increased robustness of the system performance

2.3 In "Local Feature Image Fusion Algorithm Based on Wavelet Transform"

An image fusion algorithm based on multi-scale wavelet transform according to image local features was put forward in this paper. Wavelet multi-scale decomposition was performed on original images and different wavelet coefficients could be obtained. Different fusion rules were applied to low-frequency and high-frequency coefficients. Local mean was computed in low-frequency area, which was taken as weigh to fuse low-frequency coefficients. And local information entropy was calculated in high-frequency region to fuse high-frequency coefficients. The fused image could be obtained by performing inverse wavelet transform. Standard deviation, average-gradient, entropy and mutual information were used as evaluation index to analyze the fused image. The experiment results show that the fused image had good clarity and contrast. The algorithm proposed in this paper was feasible.

3. DIGITAL IMAGE PROCESSING

Digital image processing is an area characterized by the need for extensive experimental work to establish the viability of proposed solutions to a given problem. An important characteristic underlying the design of image processing systems is the significant level of testing & experimentation that normally is required before arriving at an acceptable solution. This characteristic implies that the ability to formulate approaches &quickly prototype candidate solutions generally plays a major role in reducing the cost & time required to arrive at a viable system implementation.

What is DIP?

An image may be defined as a two-dimensional function f(x, y), where x & y are spatial coordinates, & the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y & the amplitude values of f are all finite discrete quantities, we call the image a digital image. The field of DIP refers to processing digital image by means of digital computer. Digital image is composed of a finite number of elements, each of which has a particular location & value. The elements are called pixels.

Vision is the most advanced of our sensor, so it is not surprising that image play the single most important role in human perception. However, unlike humans, who are limited to the visual band of the EM spectrum imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate also on images generated by sources that

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humans are not accustomed to associating with image.

What Is an Image?

An image is represented as a two dimensional function f(x, y) where x and y are spatial co-ordinates and the amplitude of 'f' at any pair of coordinates (x, y) is called the intensity of the image at that point.

Multiwavelet

Wavelet analysis is a new development field of applied mathematics and engineering sciences. Because of the good time-frequency localization characteristics, scale variation characteristics and direction characteristics, wavelet has been widely used in many fields. In 1994, Goodman and others established the multiwavelet basic theoretical framework based on the multi-resolution analysis In recent years, multiwavelet research has become a hot research topic in the wavelet field. Multiwavelet is an extension from scalar wavelet. It not only maintains the good time-domain and frequency domain localization properties which scalar wavelet possess, but also overcomes the shortcomings of the scalar wavelet. Compared with the scalar wavelet transform, multi-wavelet transform has the following advantages. Multiwavelet posses many desired properties such as short support, orthogonality, symmetry and smoothness which are very important for the image analysis and processing. Multiwavelet filter banks have no strict division of low-pass and high-pass. Through the multi-wavelet profiteering, it can transfer high-frequency energy to the low-frequency [2]. This is very beneficial to improve the compression ratio. There is increasing concern about the multiwavelet for the theoretical advantages and potential applications. The commonly used multiwavelets involve orthogonal multiwavelet such as GHM,CL,SA4 and biorthogonal multiwavelet such as BIGHM. In this paper, we use GHM and CL multiwavelet to process the image

A wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal.

For example, a wavelet could be created to have a frequency of Middle C and a short duration of roughly a 32nd note. If this wavelet were to be convolved at periodic intervals with a signal created from the recording of a song, then the results of these convolutions would be useful for determining when the Middle C note was being played in the song. Mathematically, the wavelet will resonate if the unknown signal contains information of similar frequency - just as a tuning fork physically resonates with sound waves of its specific tuning frequency. This concept of resonance is at the core of many practical applications of wavelet theory.

As a mathematical tool, wavelets can be used to extract information from many kinds of data, including - but certainly not limited to - audio signals and images. Sets of wavelets are generally needed to analyze data fully. A set of "complementary" wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible. Thus, sets of complementary wavelets are useful in wavelet-based compression/decompression algorithms where it is desirable to recover the original information with minimal loss.

4. PROPOSED SYSTEM

The field of digital image processing began to develop when it was affiliated with the newspaper industry in the early 1920s. The quality of digital images is one of the biggest issues in this area. There is a disturbance in all of the image's grey intensity levels. While the processing of digital images has advanced dramatically since this picture, it still faces many challenges today. Either during image processing or transmission or both, the primary source of noise in digital images appears. Relay for image acquisition on imaging sensors sensitive to bright light. The function of the light receptors located within the human eye inside the retina membrane is the same. For example, Charge-coupled (CCD) imaging equipment, which is a type of camera sensor, contains a sensor presented as a 2-D array of several million small solar cells. In this grid, every cell corresponds to a pixel in the digital image.

The light from the object is reflected in the grid of the sensor, enabling the solar cells to estimate the projected number of photons in each cell. Finally, each of these calculated charges is converted into a digital pixel value by the analog-to-digital converter (ADC). In more detail, a high photon estimated value, which is converted to a high intensity value, is provided by the cell in the sensor subjected to more light. The pixel will have a value similar to 255 (white) in grey scale images, and vice versa. Logically, to perfectly fit the scene, increasing the number of cells in the sensor improves the resolution and accuracy of the information in the image. However, because of many factors, this is not a hundred percent true. On the one side, a number of variables, such as light levels and sensor efficiency, are involved in the image acquisition environment. These factors influence the calculation of the final pixel values in the images, causing the appearance of noise and artifacts in the image.

On the other hand, image transmission through wired or wireless networks, due to atmospheric conditions or usually flows in the medium of transformation, induces variations in the real pixel values. Noise is split into two types: dependent and autonomous noise. Like multiplicative noise, based noise depends on the pixel value. Although independent noise, including white Gaussian noise, Rayleigh noise, gamma noise, exponential noise, and salt-and -pepper noise, is not associated with the pixel strength.

By generating an array that is close in size to the image given, different noise models are simulated. Except for salt and pepper noise, the strength values are stochastic numbers with a particular probability density function. Dealing with noisy images is a much harder issue in real-world applications. Next, the captured images typically involve several models of

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noise. Images obtained from satellite imagery, for example, include speckle noise, Gaussian noise, and impulse noise. Secondly, it needs prior knowledge of the noise model(s) present in the picture to choose the best denoising method. Finally, assuming that the noise model is understood, several of the existing methods of denoising cause either loss, blurring, disruption in smooth areas or ringing artifacts around the edges in some of the image information. One of the most common forms of noise in images is additive white Gaussian noise (AWGN). AWGN is distributed over images randomly.

To address this issue, an effective method for image denoising using non-local means with packing of multi patches (NLM-PMP) in non-subsampled contourlet (NSC) domain is proposed, which works based on multi-scale decomposition and directionality. It is utilized to further process the obtained denoised image for mitigation of ringing artifacts those are invariably appeared, which leads to the local structure preservation like textures, edges, and small details efficiently. The performance of the proposed hybrid technique is tested on greyscale images, and it works well at low-noise strengths. The experimental results compared with several state-of-the-art techniques demonstrate the comX-RAYitiveness of the proposed approach at lower noise strength, while yielding better performance at a lower value of σ.

4.1 Denoising using NLM-PMP in NSC domain

Image denoising using NLM-PMP in NSC domain is proposed. In addition, it is utilized to enhance the denoised image visual quality by mitigating the ringing artifacts. Fig. 1 demonstrates that the proposed image denoising framework. NSCT utilized for obtaining the multi-scale decomposition and multi directional coefficients which provides the spatial and spectral information at different scales and different directions as well. This motivates the authors to utilize both the NSCT and NLM-PMP for getting the enhanced denoising performance even at higher noise levels with improved qualitative performance both in terms of quality assessment and visual perception with enhanced textured regions. Further, it is utilized for better preservation of local structures like edges, textures and small details.

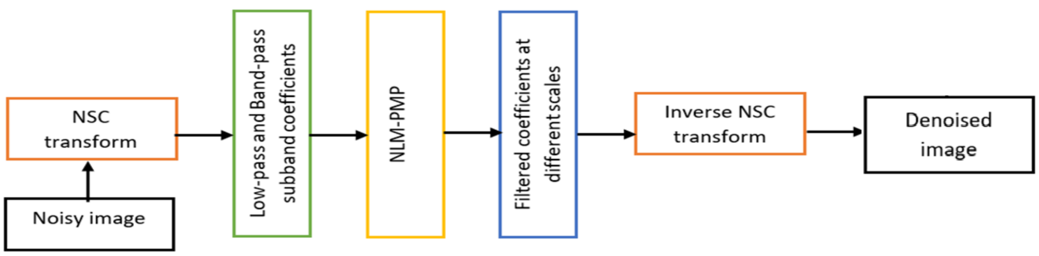

Fig. 1: NLM-PMP in NSC domain image denoising framework.

Algorithm 1: hybrid image denoising using NLM-PMP in NSC

Step 1: Select and read a noisy image

Step 2: Apply NSC transform to decompose the noisy image using non-subsampled Laplacian pyramid filter banks for multi scale decomposition and non-subsampled directional filter bank for multi dimensionality.

Step 3: Obtain the low pass subband and band-pass subband directional coefficients from the NSCT framework.

Step 4: Filter the coefficients of NSCT using NLM-PMP methodology.

Step 5: Obtain filtered coefficients at different scale regions using NSCT and NLM-PMP approaches.

Step 6: Apply inverse NSC transform to obtain the spatial filtered output and generates the final enhanced and denoised outcome.

4.2 non-local means

The major working property of NLM is effective as it calculates the weighted average of al pixels within the region. Here, exponential functionality is used to decompose the weights based on the similarity between pixels. Consider V_i is noise added in the image and U_i is original pixel value for the range of $i = 1,2,\ldots,M$. Here, M indicates the total number of available pixels. Thus, the noisy pixel is generated by adding the noise to the original image and resulted in outcome $U_i + V_i = Z_i$. Then, the resultant outcome is generated by applying NLM as follows:

$$\widehat{Z_i} = \frac{1}{C}\sum_{j \in N_i} W_{ij} Z_j \qquad (1)$$

Here, search window is denoted by N_i in the center region i. usually, the search window size as maximum and it is choose based on the weight coefficients $\{W_{ij} | j \in N_i\}$. Here, the $W_{ij}$is an important emphasizing function, which is used to reduce improve distance between pixels in U_i and U_j. Then, NLM calculates the noise based on the squared Euclidean distance measurement. Thus, the squared Euclidean distance among two consecutive pixels is used to calculate for analyzing the noise as follows:

$$D_{pixel}(Z_i, Z_j) \stackrel{\text{def}}{=} (Z_i - Z_j)^2 - 2\sigma^2 \qquad (2)$$

NLM applies this distance like patch manner on every region of image and noise levels of each patch will be compared and eliminates the high intensity noise. Then, the patches with higher noise levels having the same patch center and the distance between various noise patches is calculated as follows:

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$$D_{patch}(Z_i, Z_j) \stackrel{\text{def}}{=} \sum_{k=1}^{d} \left(Z_i(k) - Z_j(k)\right)^2 - 2d\sigma^2 \quad (3)$$

Here, $Z_j(k)$ and $Z_i(k)$ are the different patches located at center position for every $j_{th}$and i_{th} pixels, respectively. The total number of pixels in the patch is denoted by d. Then, the NLM applies the exponential weight function on the noisy image as follows:

$$W_{ij} \stackrel{\text{def}}{=} exp\left(-\frac{max\{D_{patch}(Z_i, Z_j), 0\}}{d\sigma^2 T^2}\right) \quad (4)$$

Here, normalization is denoted by $d\sigma^2$, decay parameter is denoted by T. then, the maximization is used to make total distance as 1. Thus, each pixel of image is denoised by using above process with respect to patch wise manner Then, the two patches weight function is used to calculate the total noise in the image. Then, the search window is applied on all patches of image.

4.3 Non-subsampled contourlet transform

Contourlet transform (CT) is an advanced method, which is utilizes the two-dimensional transformation. CT utilizes both the properties of curvelet transform and human visual system. Thus, the image is divided into multiple bands with maximum number of properties like directionality, critical sampling, localization, anisotropy and multiresolution, respectively. The CT operates based on the properties of directionality and multi scaling and develops the image contours by gathering the similar number of pixels. The curvelet transform is specifically utilized for generating the smoothness in the image. The curvelet transform also generates the various direction of contours and stretched shapes in the image. But the curvelet transform is developed for non-discrete continuous domain data changes the directions of rectangular grid, respectively. Thus, the CT is developed with the discrete domain properties with multi directionality and multi resolution characteristics.

Then, the directional filter bank (DFB) and Laplacian pyramid (LP) are used in the CT To achieve all this functions. Here, the DFB is a double filter bank prototype, and it is also treated as pyramid directional filter bank (PDFB). Then, the LP is used to decompose the image into multiple bands, such as band-pass image will be generated. Thus, the LP avoids the frequency overlapping and scrambling problems in the image. The PDFB is specifically utilized for higher order frequencies, because it avoids the low frequency components at all the directional subgroups.

But the CT contains some drawbacks, that is the CT is suffering with the shift invariance problem. Because up and down sampling coefficients are developed in the filter banks during the sub-band grouping process. Thus, non-subsampled filter bank (NSFB) is used to overcome this problem in the CT, which exhibits the directional and multiscale characteristics. Thus, the PDFB and LP are replaced with the NSFB in the CT and formed as NSCT, respectively.

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Fig. 2 presents the detailed operation of NSDFB and NSPFB and its integration also presented. The PDFB are applied in the edges of LP to effectively perform the operation of NSCT. Then, the NSCT decompose the image into multiple number of NSDFB bands and forms a tree structure. This tree structure avoids the aliasing effect; thus, the pixels are not overlapped. Thus, the upper and lower sub bands are perfectly synchronized without collision. Usually, the size of pyramid plays the major role in the decomposition process. if the decomposition done accurately, then the region is treated as the good label. If the decomposition done imperfectly, then the region is treated as the bad label. From this labeling, it is observed that high pass filtering is effectively used to filter the bad region label with perfect edges. Then, the low pass filtering is used to filtering the good labelling pixels. This high pass and low pass filters are concatenated together and formed as the NSDFB filtering mechanism.

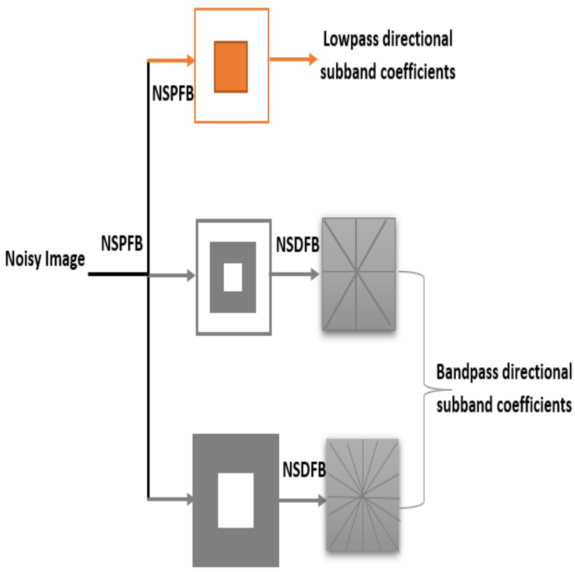

Fig. 2: Structure of NSCT framework with the integration of NSPFB and NSDFB.

4.4 Non-local means with packing of multiple patches (NLM-PMP)

The NLM-PMP is based on the idea of separable filtering which is common in the image processing literature. These filters are not separable since they can't execute the process of filtering by fast processing of columns and rows (as can be done for linear filters with separable kernels). As a matter of fact, filtering results of row adopted by column result is ideally dissent from the results obtained by the operations done in reversible manner. Therefore, in our proposal authors considered both the possibilities into account and derived the denoised output image as these primitive's optimization. The optimality is in the sense of a certain replacement of the mean-squared error that is popularly referred to as Stein's unbiased risk estimator which resolves the 2×2 linear system. The methodology presented in this is differ from that the separable bilateral algorithm and gives much better results of denoising framework.

The major novelty of NLM-PMP, however, is the proposal of an algorithm that can reduce the complexity of one-dimensional NLM from $O(NSK)$ to $O(NS)$, where N is the length of the signal. This is established on the reflection that the distances of patch regarded in the NLM of a one-dimensional signal can be calculated from $O(NS)$ entries of a matrix which is specially implanted, which is found by applying a box or Gaussian filter along the matrix sub diagonals which is computed through lifting, namely, via the tensor product of the signal with itself. As is well-known, box and Gaussian filtering

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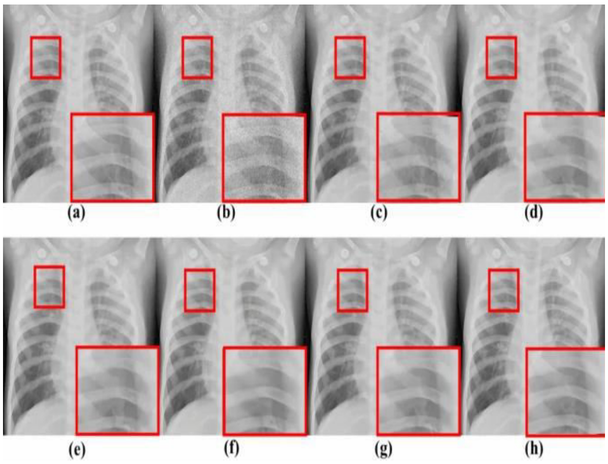
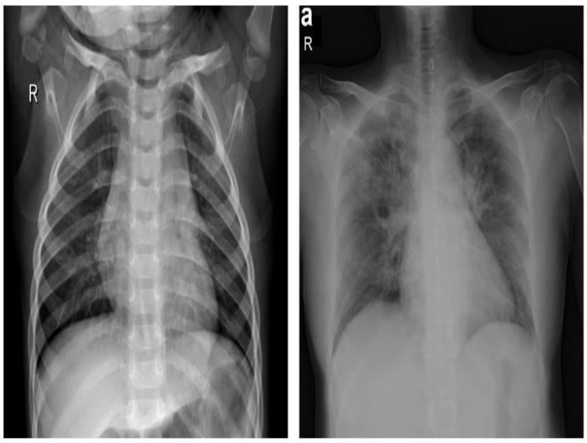
can be performed using $O(1)$ operations with respect to the filter length.

The NLM-PMP algorithm as an outcome need O(NS) operations to calculate the full patch set distances in NLM. To the best of author knowledge, the observation that lifting can be utilized for efficiently calculating the distances of patch is novel. We further utilize this lifting-based algorithm to implement a fast-separable NLM formulation for the images of 2D i.e., grayscale images. The proposed NLM-PMP complexity is $2N \times O(NS) = O(N^2S)$ for an $N \times N$ image, which is substantially smaller than the $O(N^2S^2K^2)$ complexity of standard NLM.

5. RESULTS





(a) Normal (b) COVID-19

6. CONCLUSION

We proposed a separable formulation of non-local means and a fast algorithm for the same. The algorithm admits a simple implementation for both box and Gaussian kernels. The overall complexity of the algorithm is smaller than that of existing fast implementations of NLM. In fact, the actual run-time of the Matlab implementation of the algorithm is comX-RAYitive with the run-time of existing implementations, particularly when the patch size and the search window are large. The speedup over NLM was observed to be at least 300 times. We also demonstrated that the denoising performance of the proposed algorithm s consistently better than NLM and some of its variants in terms of PSNR/SSIM and the visual quality. It is clear that the SNLM has a straightforward extension to video and volume data, where the acceleration would be even more significant.

6.1 Future scope

Multimodality medical image fusion have an important role in improving medical diagnosis, but real problem is to obtain visually enhanced images through fusion technique. In this thesis hybrid image fusion techniques are proposed. The main objective of this thesis was to design hybrid image fusion algorithm. The first technique was hybrid of wavelet transform and other was hybrid of dual tree dwt transform. Hybrid image fusion approach proved to be useful over other individual approaches as it encompasses all the advantages of individual image fusion transforms and provides a clearer and more enhanced image having more details than that of the individual images. It is clear from previous results that hybrid image fusion techniques are successful in medical diagnosis.

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