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Based on Artificial Neural Network Reconstructing Fast X-Ray and CT images.

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ABSTRACT

Over the past two decades, rapid system and hardware development of x-ray computed tomography (CT) technologies has been accompanied by equally exciting advances in image reconstruction algorithms. The algorithmic development can generally be classified into three major areas: analytical reconstruction, model-based iterative reconstruction, and application-specific reconstruction. In this paper, we focus on solving regularized (weighted) least-squares problems using a linearized variant of the AL method that replaces the quadratic AL penalty term in the scaled augmented Lagrangian with its separable quadratic surrogate (SQS) function, thus leading to a much simpler ordered-subsets (OS) accelerable splitting-based algorithm, OS-LALM, for X-ray CT image reconstruction. To further accelerate the proposed algorithm, we use artificial neural network based analysis for image reconstruction under conditions such as few-view and limited angle data. Experimental results show that the proposed algorithm significantly accelerates the “convergence” of X-ray CT image reconstruction.

Keywords: OS-LALM; X-ray; computed tomography; PSNR

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INTRODUCTION

X-ray computerized tomography (CT) is the most widespread and significant method utilized in medicine. Generally, the tomographic images are observed by an appropriate image reconstruction and a method of projection acquisition algorithm. The main problem occurring in CT is image reconstruction from projections which can be observed in an X-ray scanner. There are numerous reconstruction methods are avail to overcome this problem. The most significant reconstruction methods are facilitating back-projection, convolution [1-3] and the algebraic reconstruction technique (ART) [4-7]. Moreover, these methods provide some alternative reconstruction methods. The most popular of emphasis like to be neural network-based algorithms. Neural networks are utilized in various implementations, for instance, in image processing [8-10], in general in computerized tomography. Form the literature survey, more number of works has been reported in reconstruction algorithms based on supervised neural networks [11-14]. Based on recurrent neural networks, Algebraic method for image reconstruction from projections is also investigated by many authors [15-17].

Computed tomography imaging gives a defects map of the scanned object with continuously irradiating by X-rays from various directions. The integral defects of the X-ray, measured with the help of comparing the radiation intensity leaving and entering the body, develop the raw information for the computed tomography imaging. In general, the measurements of photon count may be degraded by stochastic noise, practically modeled as instances of Poisson random variables [18]. Different such algorithms available, ranging from simple and most popular Filtered-Back-Projection (FBP) [19], including more advanced Bayesian-inspired iterative algorithms [20], [21] that take unknown image into an account and the statistical nature of the measurements. Since, computed tomography relies on X-ray, which is an ionizing radiation is more dangerous to living tissues, there is a constant and dire to enhance the reconstruction algorithms by reduce radiation dose. In the present study, the Artificial Neural Network technique is utilizing for convergence the X-ray CT image. This technique can reduce the huge dynamic loss in the least subset squares and computed the error of the image of the X-ray CT image.

COMPUTATIONAL AND PROPOSED METHODS

MATLAB (MATRIX LABORATORY) is a programming language for technical computing from the math works, Natick, MA. It is used for a wide variety of scientific and engineering calculation, especially for automatic control and signal processing. Matlab runs on windows, Mac and a variety of unit based systems Developed by Cleve Moler in the late of 1970's and based on the original LINPACK and EISPACK FORTRAN libraries, it was initially used for factoringmatrices and solving linear equations. Moler commercialized the product with two colleagues in 1984. MATLAB is also noted for its extensive graphics capabilities.

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. Figure 1 shows the block diagram of proposed Artificial Neural Network.

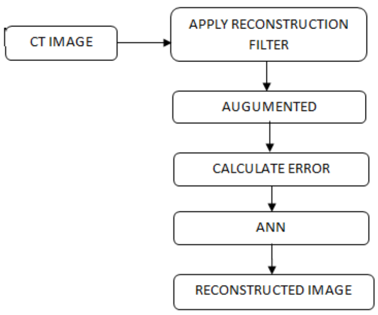

Fig 1. BLOCK DIAGRAM of proposed ANN

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RESULTS AND DISSCUSION

In the Artificial Neural Network the real time X-Ray Computed Tomography image can be given as the input of the algorithm. It will be get converted the image analog signal to digital signal weather the digital signal to analog signal by applying the image reconstruction filter. This will be taken as the input for the Artificial Neural Network.

Contrast-limited adaptive histogram equalization (CLAHE) was originally developed for medical imaging and has proven to be successful for enhancement of low-contrast images such as portal films. The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible. The full grey spectrum is used to express the image. Contrast Limited Adaptive Histogram Equalization, CLAHE, is an improved version of AHE, or Adaptive Histogram Equalization. Both overcome the limitations of standard histogram equalization. A variety of adaptive contrast-limited histogram equalization techniques (CLAHE) are provided. Sharp field edges can be maintained by selective enhancement within the field boundaries. Selective enhancement is accomplished by first detecting the field edge in a portal image and then only processing those regions of the image that lie inside the field edge. Noise can be reduced while maintaining the high spatial frequency content of the image by applying a combination of CLAHE, median filtration and edge sharpening. This technique known as Sequential processing can be recorded into a user macro for repeat application at any time. A variation of the contrast limited technique called adaptive histogram clip (AHC) can also be applied. AHC automatically adjusts clipping level and moderates over enhancement of back ground regions of portal images. Figure 2 and 3 refers the image obtained before and after clahe respectively.

Fig 2. Before clahe

Fig 3. After clahe

Primary colours is a useful fact that the huge variety of colours that can be perceived by humans can all be produced simply by adding together appropriate amounts of red, blue and green colours. These colours are known as the primary colours. Thus in most image processing applications, colours are represented by specifying separate intensity values for red, green and blue components. This representation is commonly referred to as RGB. The primary colour phenomenon results from the fact that humans have three different sorts of colour receptors in their retinas which are each most sensitive to different visible light wavelengths. The primary colours used in painting (red, yellow and blue) are different. When paints are mixed, the `addition' of a new colour paint actually subtractswavelengths from the reflected visible light.

Colour images are possible to construct all visible colours by combining the three primary colours red, green and blue, because the human eye has only three different colour receptor, each of them sensible to one of the three colours. Different combinations in the stimulation of the receptors enable the human eye to distinguish approximately 350,000 colours. A RGB colour image is a multi-spectral image with one band for each colour red, green and blue, thus producing a weighted combination of the three primary colours for each pixel. A full 24-bit colour image contains one 8-bit value for each colour, thus being able to display different colours. However, it is computationally expensive and often not necessary to use the full 24-bit to store the colour for each pixel. Therefore, the colour for each pixel is often encoded in a single byte, resulting in a 8-bit colour image. The process of reducing the colour representation from 24-bits to 8-bits, known as colour quantization, restricts the number of possible colours to 256. However, there is normally no visible difference between a 24-colour image and the same image displayed with 8 bits. A 8-bit colour images are based on colourmaps, which are look up tables taking the 8 bit pixel value as index and providing an output value for each colour.

In order for any digital computer processing to be carried out on an image, it must first be stored within the computer in a suitable form that can be manipulated by a computer program. The most practical way of doing this is to divide the image up into a collection of discrete (and usually small) cells, which are known as pixels. Most commonly, the image is divided up into a rectangular grid of pixels, so that each pixel is itself a small rectangle. Once this has been done, each pixel is given a pixel value that represents the colour of that pixel. It is assumed that the whole pixel is the same colour, and so any colour variation that did exist within the area of the pixel before the image was discretized is lost. However, if the area of each pixel is very small, then the discrete nature of the image is often not visible to the human eye. Other pixel shapes and formations can be used, most notably the hexagonal grid, in which each pixel is a small hexagon. This has some advantages in image processing, including the fact that pixel connectivity is less ambiguously defined than with a square grid, but hexagonal grids are not widely used. Part of the reason is that many image capture systems intrinsically discretize the captured image into a rectangular grid in the first instance.

Each of the pixels that represent an image stored inside a computer has a pixel value, which describes how bright that pixel is, and/or what colour it should be. In the simplest case of binary images, the pixel value is a 1-bit number indicating either foreground or background. For a grey scale images, the pixel value is a single number that represents the brightness of the pixel. Often this number is stored as an 8-bit integer giving a range of possible values from 0 to 255. Typically zero is taken to be black, and 255 is taken to be white. Values in between make up the different shades of grey. To represent colour images, separate red, green and blue components must be specified for each pixel (assuming an RGB colourspace), and so the pixel `value' is actually a vector of three numbers. Often the three different components are stored as three separate `greyscale' images known as colour planes(one for each of red, green and blue), which have to be recombined when displaying or processing.

Multi-spectral images can contain even more than three components for each pixel, and by extension these are stored in the same kind of way, as a vector pixel value, or as separate colour planes. The actual greyscale or colour component intensities for each pixel may not actually be stored explicitly. Often, all that is stored for each pixel is an index into a colourmap in which the actual intensity or colours can be looked up. Although simple 8-bit integers or vectors of 8-bit integers are the most common sorts of pixel values used, some image formats support different types of value, for instance 32-bit signed integers or floating point values. Such values are extremely useful in image processing as they allow processing to be carried out on the image where the resulting pixel values are not necessarily 8-bit integers. If this approach is used then it is usually necessary to set up a colour map, which relates particular ranges of pixel values to particular displayed colours.

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Brightness makes the image lighter or darker overall, while Contrast either emphasizes or de-emphasizes the difference between lighter and darker regions. Contrast is easy to understand visually. Artistically, contrasting colors are colors that are opposite on the color wheel colors that are opposites. In a high contrast image, you can see definite edges and the different elements of that image are accented. In a low contrast image, all the colors are nearly the same and it's hard to make out detail. Contrasting colors in terms of a computer's representation of an image, means the "primary colors" or the colors with color components of 0 or 255 (Min and Max). Black, White, Red, Green, Blue, Cyan, Magenta, and Yellow are the high contrast colours. When all the colors in an image are around one single color, that image has low contrast. Grey is the usual color of choice because it rests exactly in between 0 and 255 (127 or 128).

Describing colors using hue, saturation and brightness is a convenient way to organize differences in colors as perceived by humans. Even though color images on computer monitors are made up of varying amounts of Red, Green and Blue phosphor dots, it is at times more conceptually appropriate to discuss colors as made up of hue, saturation and brightness than as varying triplets of RGB numbers. This is because human perception sees colors in these ways and not as triplets of numbers.

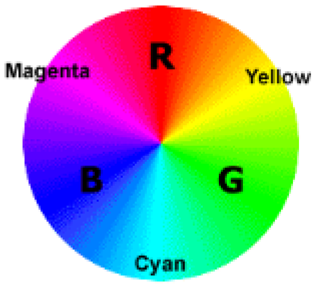

Fig 4. Red Green Blue

If we imagine the three primary colors red, green and blue placed equally apart on a color wheel, all the other colors of the spectrum can be created by mixes between any two of the primary colors. For example, the printer's colors known as Magenta, Yellow, and Cyan are mid-way between Red and Blue, Red and Green and Blue and Green respectively.

This diagram is called the color wheel, and any particular spot on the wheel from 0 to 360 degrees is referred to as a hue, which specifies the specific tone of color as shown in Figure 4. "Hue" differs slightly from "color" because a color can have saturation or brightness as well as a hue.

Saturation is the intensity of a hue from gray tone (no saturation) to pure, vivid color (high saturation).

Brightness is the relative lightness or darkness of a particular color, from black (no brightness) to white (full brightness). Brightness is also called Lightness in

Histogram equalization is one of the well-known en-hancement techniques. In histogram equalization, the dynamic range and contrast of an image is modified by altering the image such that its intensity histogram has a desired shape. This is achieved by using cumulative distribution function as the mapping function. The intensity levels are changed such that the peaks of the histogram are stretched and the troughs are compressed. If a digital image has N pixels distributed in L discrete intensity le-vels and nk is the number of pixels with intensity level and then the probability density function (PDF) of the image. Though this method is simple, it fails in myocardial nuclear images since the gray values are physically far apart from each other in the image. Due to this reason, histogram equalization gives very poor result for myo-cardial images.

DEGRADATION

In the biological neural network are spectacularly more energy efficient than currently available man-made, transistor-based information processing units. Additionally, biological systems do not suffer catastrophic failures when subjected to physical damage, but experience proportional performance degradation as shown in Figure 5. In the Artificial Neural Network has the high advantage to make the images in information processing unit might be inherently parallel or are deployed in an environment where the processing unit susceptible to physical damage, this intended to the network applications, present analysis of performance degradation of various architectures of artificial neural network when subjected to stuck at 0 and stuck at 1 faults. This study to determine if a fixed number of neurons should be kept in a single or multiple hidden layers. Faults are administered to input and hidden layers and analysis of un optimized and optimized, feed forward and recurrent networks, trained with uncorrelated and correlated data sets is conducted. A comparison network with single, dual, triple, and quadruple hidden layers is quantified. This main finding is that stuck at 0 faults administered to input layer result in least performance degradation in network with multiple hidden layers. However, for stuck at 0 faults occurring to cells in hidden layers, the networks that offer the architecture that sustains the least damage is that of single hidden layer. When stuck at 1 errors are applied to either input or hidden layers that offer the most resilience are those with multiple hidden layers. The suggest's that Artificial Neural Network architecture should be subjected to, namely damage to sensors or the Neural Network itself. It make the salt and pepper color image.

Fig 5. Degradation image

IMPROVED BILATERAL

It is a challenging problem to suppress mixed noise in color images. The traditional bilateral filter an excellently reduce additive noise without destroying image edges and details, but it fails to remove impulsive noise. This improved bilateral filtering method can simultaneously suppress both impulsive and additive noise as shown in Figure 6. The proposed solution first introduced a new weighting function to the bilateral filtering mechanism, which is experimentally more effective than the traditional Gaussian kernel. Then, either the current pixel or the vector median, instead of always the current pixel itself, is chosen as the base to take part in the bilateral filtering action, which is determined by whether the current pixel is a possible impulse or not. This show that it will remove the salt and pepper noise in the X-Ray CT image.

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Fig 6. Improved bilateral filter image

AUGMENTED LAGRANGAIN

Augmented Lagrangian method is one of the algorithms in a class of methods for constrained optimization that seeks a solution by replacing the original constrained problem by a sequence of unconstrained sub problems. Also known as the method of multipliers, the augmented Lagrangian method introduces explicit Lagrangian multiplier estimates at each step.

Figure 7 refers the augmented Lagrangian (AL) method that solvesconvex optimization problems with linear constraints has drawn more attention recently in imaging applications due to its decomposable structure for composite cost functions andempirical fast convergence rate under weak conditions. However, for problems such as X-ray computed tomography (CT) image reconstruction and large-scale sparse regression with “big data”, where there is no efficient way to solve the inner least-squares problem, the AL method can be slow due to the inevitable iterative inner up dates. In this paper, we focus on solving regularized (weighted) least-squares problems using a linearized variant of the AL method that replaces the quadratic AL penalty term in the scaled augmented Lagrangian with its separable quadratic surrogate (SQS) function, thus leading to a much simpler ordered-subsets (OS) accelerable splitting-based algorithm, OS-LALM, for X-ray CT image reconstruction. To further accelerate the proposed algorithm, we use a second-order recursive system analysis to design a deterministic downward continuation approach that avoid stedious parameter tuning and provides fast convergence. Experimental results show that the proposed algorithm significantly accelerates the “convergence” of X-ray CT image reconstruction with negligible overhead and greatly reduces the OS artifacts in the reconstructed image when using many subsets for OS acceleration

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Fig 7. Augmented Lagrangian

ERROR CALCULATION

The error calculation is used with supervised learning, is the technique of comparing the system output to the desired output value, and using that error to direct the training. In the most direct route, the error values can be used to directly adjust the tap weight , using an algorithm such as the backpropagation algorithm. If the system output is y, and the desired system output is known to be d, the error signal can be defined as:

$$e = d - y$$

Error correction learning algorithms attempt to minimize this error signal at each training iteration as referred in Figure 8. The most popular learning algorithm for use with error-calculation learning is the back propagation algorithm.

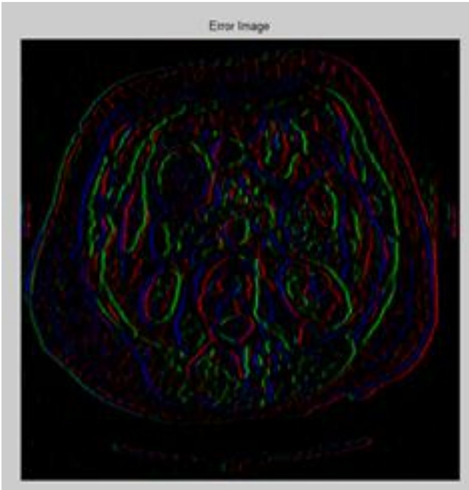

Fig 8. Error image

The Error Rate Calculation block compares input data from a transmitter with input data from a receiver. It calculates the error rate as a running statistic, by dividing the total number of unequal pairs of data elements by the total number of input data elements from one source.

Artificial Neural Network

In machine learning and cognitive science, artificial neural networks (ANNs) are a family of models inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning. It will also calculate the peak signal to noise ratio to justifies the image will be quality image. Table 1 refers the comparison of the peak signal to noise ratio (PSNR) image between the Augmented Lagrangian and ANN. Thus, the peak signal to noise ratio value is observed greater than 35 for ANN leads to enhance the performance of X-ray CT image. Table 1 represents the comparison statement of PSNR between ANN and Augmented Lagrangian.

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Fig 9. PSNR for Artificial Neural Network

Table 1 Comparison statement of PSNR

PSNR Image	Augmented Lagrangian	Artificial Neural Network
Image 1	15.324	35.6774
Image 2	20.741	35.234

CONCLUSION

The Artificial Neural Network has the powerful technique which is used to convergence the X-ray CT image. It will reduce the huge dynamic loss in the least subset squares and computed the error of the image of the X-Ray CT image. In this algorithm takes several input at the same time and perform all the inputs according to them the neural network will take the best image as a input to perform the algorithm. It will reduce the time duration of the computed tomography. The error calculation will occur between the inputs of the transmitter to the input of the receiver. Then the time duration of the error calculation is calculated and surveyed for the errors occurs in the X-ray CT images. Therefore, the peak signal to noise ratio (PSNR) value will be calculated and the value should be greater than or equal to 35.

REFERENCES

[1] Jain AK, Fundamentals of digital image processing. Prentice Hall, New Jersey 1989.
[2] Ramachandran GN, Lakshminarayanan AV, Proc Natl Acad Sci USA 1971; 68:2236–2240.
[3] Lewitt RM, Proc IEEE 1983;71(3):390–408.
[4] Censor Y, Proc IEEE 1983;71(3):409–419.
[5] Jaene B, Digital image processing—concepts. Algoritms and scientific applications. Springer, Berlin 1991.
[6] Gordon R, Bender R, Herman GT, J Theor Biol 1970;29:471–481.
[7] Kaczmarz S, Bull Acad Polon Sci Lett A 1937;35:355–357.
[8] Tadeusiewicz R, Comput Methods Mater Sci 2010;10(1):1–7.
[9] Rutkowski L, Cierniak R, Int J Appl Math Comput Sci 1996;6(3):431–445.
[10] Cierniak R, Rutkowski L, Image Process Commun 2000;2(4):29–36.
[11] Yau SF, Wong SH, SPIE 1996;2664:170–179.
[12] Knoll P, Mirzaei S, Muellner A, Leitha T, Koriska K, Koehn H, Neumann M, Med Phys 1999;26:244–248.
[13] Kerr JP, Bartlett EB, Med Phys 1995;22:601–610.
[14] Munlay MT, Floyd CE, Bowsher JE, Coleman RE, Med Phys 1994;21:1889–1899.
[15] Cichocki A, Unbehauen R, Lendl M, Weinzierl K, Neurocomputing 1995;8:7–41.

[16] Wang Y, Wahl FM, IEEE Trans Neural Netw 1997;8(5):1008–1014.
[17] Srinivasan V, Han YK, Ong SH, Image Vis Comput 1993;11(5):278–282.
[18] Bian J, La Riviere PJ, Vargas P.A, IEEE Trans. Med. Imag. 2006; 2: 1022–1036.
[19] Shepp LA, Kruskal JB, The American Mathematical Monthly 1978; 85: 420–439.
[20] Lu H, Liang Z, Wang J, Li T, IEEE Trans. Med. Imaging 2006; 25:1272–1283.
[21] Elbakri IA, Fessler JA, IEEE Trans. Med. Imag. 2002; 21: 89–99.