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DE NOISING OF MEDICAL IMAGES BY USING WAVELET AND GAUSSIAN LAPLACIAN MODELS

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ABSTRACT

In this proposed method De noise the image by using image processing techniques. The de noise is very main important thing in medical image processing. After de noised only the image can we propose any other stages . In existing methods de noised only done at spatial domain. At now we proposed method mostly done at frequency domain. We use DWT (d**iscrete wavelet transform** (DWT) for decompose of the image. Then apply Gaussian and laplacian model for removing the noise from image. Finally we compare the noise model and outputs of image results for both filter models.

KEYWORDS: DWT, Gaussian and laplacian model.

INTRODUCTION

Images with high definition are desirable in many applications, including medical imaging, video surveillance, astronomy, and so on. In professional medical imaging, pictures are received for professional medical purposes, providing details about the anatomy, the physiologic as well as metabolic activities of the volume below your skin. The appearance of electronic medical imaging technologies including Computerized Tomography (CT), Positron Emission Tomography (PET), Over unity magnetic Resonance Imaging (MRI), along with combined strategies, e. h. SPECT/CT provides revolutionized contemporary medicine. Inspite of the advances throughout acquisition technology plus the performance regarding optimized reconstruction algorithms over the two previous decades, it's not necessarily easy to acquire an image at the desired resolution due to imaging conditions, the limitations of actual imaging systems along with quality-limiting factors including noise as well as blur. Noise which is inherent throughout medical imaging may decrease adversely your contrast plus the visibility regarding details that can contain vital information, thus diminishing the accuracy plus the reliability regarding pathological examination.

In your multi-image super-resolution technique, a HOURS image is actually reconstructed by simply exploiting data from diverse subpixel altered LR images of the same world. A typical solution pertaining to super-resolution from an image sequence involves three sub-tasks: enrollment, fusion as well as deblurring. The initial and biggest task of these methods is actually motion appraisal or enrollment between LR images for the reason that precision of the estimation is vital for your success of the whole technique. However, it can be difficult for you to accurately appraisal motions among multiple unreadable and deafening LR pictures in purposes involving sophisticated movements. Because of this , why multi-image structured SR methods isn't ready pertaining to practical purposes.

Many learning-based methods have been proposed along with demonstrated guaranteeing results. Some methods provide nearest neighbors search,. Throughout these techniques, each patch of the LR photograph is when compared to LR spots stored inside the database in order to extract your nearest LR patches and hence the similar HR spots. These HOURS patches are generally then used to estimate your output through different schemes. In, Freeman et al. used the Markov circle to probabilistically product relationships among HR as well as paired LR spots, and among neighboring HOURS patches with an approximate option using notion propagation. Throughout Chang et al. proposed to determine the HR patch determined by a linear combination of HR spots. For in which, after seeking the linear combination of the local LR area such it is closest to

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a given insight LR area, the result HR area is predicted by changing LR patches while using the associated HOURS patches inside the linear blend. In Betty et al. exploited the relationship between HOURS and LR area pairs determined by a regression purpose. Despite your success of the nearest neighbor-based techniques, the drawback of these methods is they highly rely on how many nearest friends. More recently, some example-based SR techniques via sparse representation have been proposed along with promising routines. Unlike your nearest neighbors based techniques, these sparse-coding-based SR methods make use of learning your sparse relationship between photograph patches, thus staying away from choosing how many nearest pixels.

SUPER RESOLUTION TECHNIQUE

The conventional and well-known interpolation techniques [1] for enhancing image resolution are unfortunately inefficient when the given low-resolution image is corrupted by noise. Moreover, these techniques may also introduce blurring, ringing, as well as aliasing artifacts. Another technique to alleviate this problem is super-resolution (SR) which consists of generating a high-resolution (HR) image from a lowresolution (LR) image, using additional information such as multiple low-resolution (LR) images or a database that learns relationship between low and high-resolution images.

A good overview of the SR methods can be found in [2]. Since the first idea was introduced by Huang and Tsai, many SR methods have been proposed and can be broadly categorized into two main groups: multi-image SR and single-image SR [3]. In the multi-image super-resolution method, a HR image is reconstructed by exploiting information from different sub pixel shifted LR images of the same scene.

HR patches in the database with two conditions:
(i) the HR estimated version should be consistent with the LR patch under consideration, and (ii) the coefficients of the sparse positive linear combination must depend on the similarity between the input LR patch and the example LR patches in the database.

To this end, an optimal model is proposed to find this combination by formulating the SR problem as a constrained optimization one with penalization realized by the proposed criterion of dissimilarity between patches.

Advantage of SR method:

The proposed SR method has some advantages as follows:

1) It can be effectively applied in both cases: the input LR image is a noiseless image or a noisy one. For the noiseless case, the database of example image pairs can be constructed directly using only this LR image.

2) Compared with the nearest neighbors-based methods, the proposed sparsity-based method is not limited by the choice of the number of nearest neighbors.

3) Unlike the conventional SR methods via sparse representation, the proposed method efficiently exploits the similarity between image patches, and does not train any dictionary.

DISCRETE WAVELET TRANSFORM

Scientists all over the globe have been working under the domain, speech recognition for last many decades. This is one of the intensive areas of research [1]. However automatic speech recognition is yet to achieve a completely reliable performance. Hence ASR has been a subject of intensive research. Recent advances in soft computing techniques give more importance to automatic speech recognition. Large variation in speech signals and other criteria like native accent and varying pronunciations makes the task very difficult. ASR is hence a complex task and it requires more intelligence to achieve a good recognition result. In abstract mathematics, it has been known for quite some time that techniques based on Fourier series and Fourier transforms are not quite adequate for many problems. Wavelet based transform techniques remains indifferent in handling such problems. We have used wavelet based feature extraction for developing a feature vector. Performance of the overall system depends on pre-processing, feature extraction and classification. Selecting a feature extraction method and classifier often depends on the available resources. In this paper we compare the results of a study that was carried out by using Discrete Wavelet Transform and Wavelet Packet Decomposition Techniques. Wavelets are functions with compact support capable of representing signals with good time and frequency resolution. The choice of Wavelet Transform over conventional methods is due their ability to capture localized features [2]. ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. Here,

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accuracy has been increased by the combination of wavelet and artificial neural network.

Feature extraction based on wavelet:

Wavelet has generated a tremendous interest in both applied and theoretical areas. The wavelet transform theory provides an alternative tool for short time analysis of quasi stationary signal such as Speech as opposed to traditional transforms like FFT. Wavelet analysis is a powerful and popular tool for the analysis of non stationary signals. The wavelet transform is a joint function of a time series of interest $x(t)$ and an analyzing function or wavelet $\tilde{A}(t)$. This transform isolates signal variability both in time t, and also in "scale" s, by rescaling and shifting the analyzing wavelet [3]. We have used wavelet based transform techniques to extract feature from very complex speech data. Feature extraction involves information retrieval from the audio signal [4]. Here we have used daubechies 4 (db4) type of mother wavelet for feature extraction purpose. Daubechies wavelets are the most popular wavelets. They represent the foundations of wavelet signal processing and are used in numerous applications. These are also called Maxflat wavelets as their frequency responses have maximum flatness at frequencies 0 and π.

Multi-Resolution Analysis using Filter Banks:

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up sampling and down sampling (sub sampling) operations [5]. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in figure 1 and 2. This is called the Mallat algorithm or Mallat-tree decomposition.

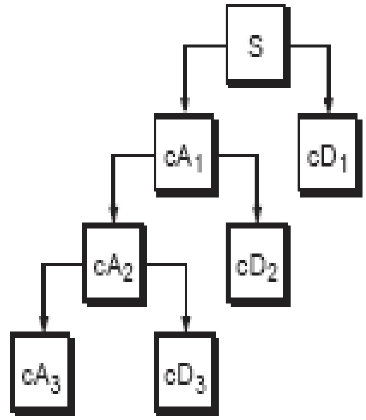

Fig 1 : Decomposition Tree

Wavelet Packet Decomposition:

Wavelet packet decomposition (WPD) (sometimes known as just wavelet packets) is a wavelet transform where the signal is passed through more filters than the DWT. Wavelet packets are the particular linear combination of wavelets. They form bases which retain many of the orthogonality, smoothness, and localization properties of their parent wavelets. The coefficients in the linear combinations are computed by a recursive algorithm making each newly computed wavelet packet coefficient sequence the root of its own analysis tree.

In the DWT, each level is calculated by passing the previous approximation coefficients though a high and low pass filters. However, in the WPD, both the detail and approximation coefficients are decomposed. Figure 3: Wavelet Packet Decomposition Tree

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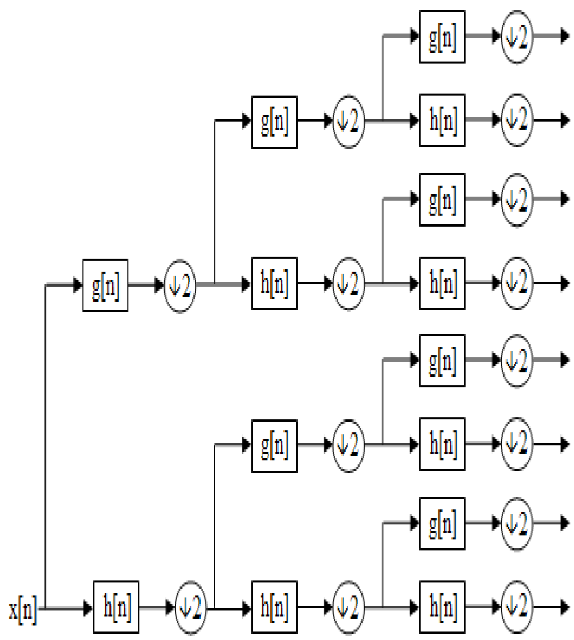

Fig 2 : Wavelet Packet Decomposition Tree

For n levels of decomposition the WPD produces 2n different sets of coefficients (or nodes) as opposed to (n + 1) sets for the DWT. However, due to the down sampling process the overall number of coefficients is still the same and there is no redundancy.

Classifications

In a general sense, a neural network is a system that emulates the optimal processor for a particular task, something which cannot be done using a conventional digital computer, except with a lot of user input. Optimal processors are sometimes highly complex, nonlinear and parallel information processing systems. Multi Layer Perception Network architecture is used for training and testing purpose. The MLP is a feed-forward network consisting of units arranged in layers with only forward connections to units in subsequent layers [4]. The connections have weights associated with them. Each signal traveling along a link is multiplied by its weight. The input layer, being the first layer, has input units that distribute the inputs to units in subsequent layers. In the following (hidden) layer, each unit sums its inputs and adds a threshold to it and nonlinearly transforms the sum (called the net function) to produce the unit output (called the activation). The output layer units often have linear activations, so that output activations equal net function values.

SYSTEM ARCHITECTURE

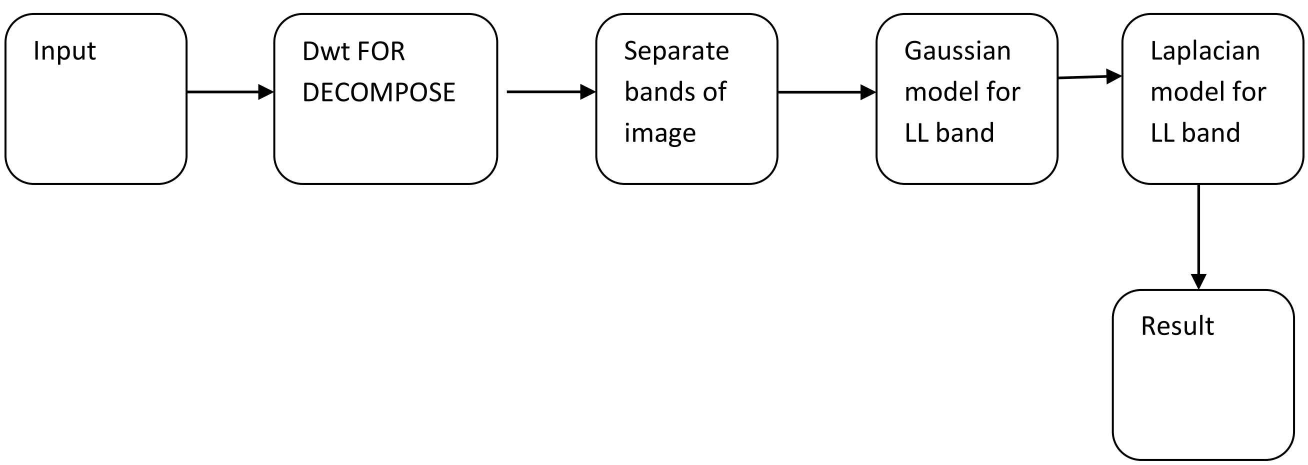

Fig 3 The Overall System Model

In above figure the overall system model is explained. First the noisy image is given as input. Then the image is decomposed by dwt method. The separate bands of images are sent to Gaussian and laplacian model for removing noise from the image. Finally we compare the noise model and outputs of image results for both filter models.

RESULTS AND DISCUSSION

From this study we could understand and experience the effectiveness of discrete wavelet transform in

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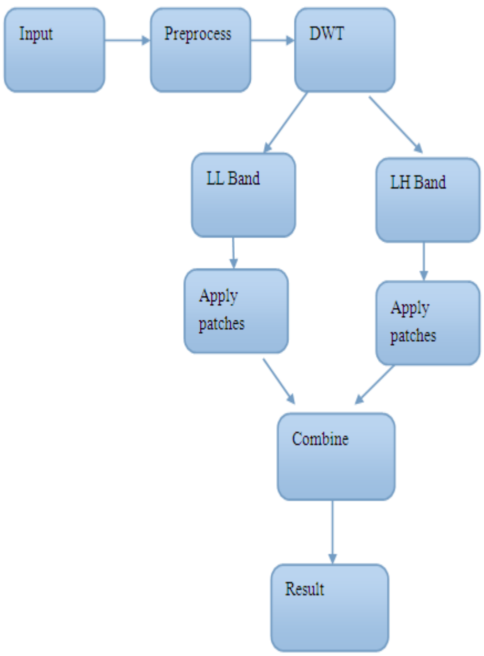
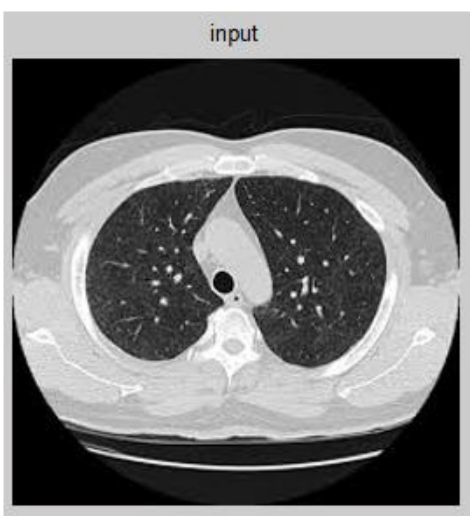
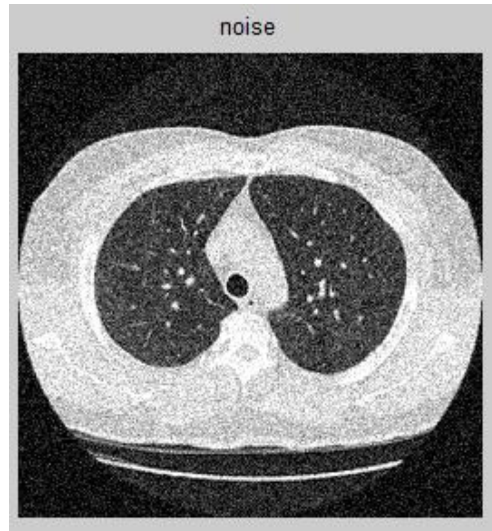
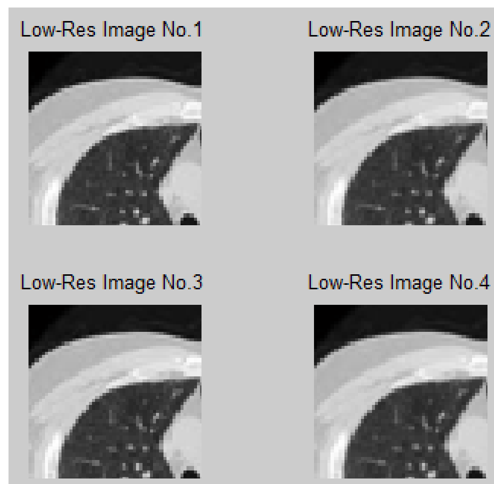
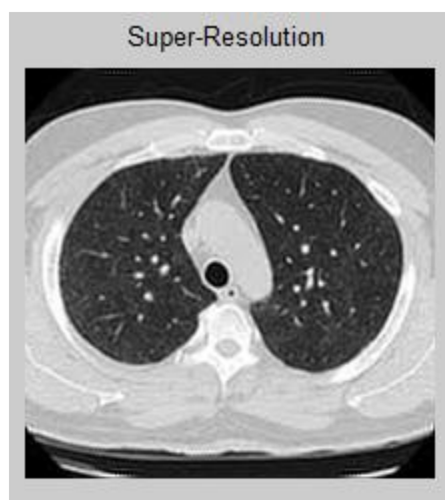
feature extraction. The performance of wavelet packet in feature extraction is not appreciable. The performance of wavelet packet is not hopeful as a feature extraction technique while comparing with the discrete wavelet transforms decomposition technique. We have also observed that, Neural Network is an effective tool which can be embedded successfully with wavelet. However, the result is encouraging one. Even though the Discrete Wavelet Based Transform technique with ANN classifier gives a very good recognition result, the efficiency of the method is to be verified with very large database.











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CONCLUSION

We proposed a model to improve the resolution of a PET image, analyzing the image using for DWT (discrete wavelet transform) and get individual patches in (LL,LH,HL,HH) coefficient of pixels and improvise each model and removing the noise using filters. From that we achieve a gain of improvisation mean square error is 93.8310 and reduce this noise and get improve output shows in peak to signal noise ratio is 28.4413 it is a reasonable value for improving of high resolution image.

REFERENCES

1. B Karthik, TVUK Kumar, Noise Removal Using Mixtures of Projected Gaussian Scale Mixtures, World Applied Sciences Journal 29 (8), 10391045, 2014.
2. D. Bailey, P. Roach, E. Bailey, J. Hewlett, and R. Keijzers, “Development of a cost-effective modular SPECT/CT scanner,” *Eur. J. Nucl. Med. Molecular Imag.*, vol. 34, no. 9, pp. 1415–1426, 2007.
3. G. Dougherty, *Digital Image Processing for Medical Applications*. Cambridge, U.K.: Cambridge Univ. Press, 2009.
4. D. Wallach *et al.*, “Super-resolution in 4D positron emission tomography,” in *Proc. IEEE Nucl. Sci. Symp. Conf.*, Oct. 2008, pp. 4285–4287.
5. N. Ben-Eliezer, M. Irani, and L. Frydman, “Super-resolved spatially encoded single-scan 2D MRI,” *Magn. Reson. Med.*, vol. 63, no. 6, pp. 1594–1600, 2010.