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# Medical Image Denoising Using Two-stage Iterative Down- up CNN and SURF FEATURES

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## ABSTRACT

Most of existing medical image denoising methods focus on estimating either the image or the residual noise. Moreover, they are usually designed for one specific noise with a strong assumption of the noise distribution. Explicitly modeling the distributions of these complex noises in the medical image is extremely hard. They cannot be accurately held by the Gaussian or mixture of Gaussian model. To overcome the two drawbacks, in this work, we propose a deep iterative down-up convolutional neural network (DIDN) for image denoising, which repeatedly decreases and increases the resolution of the feature maps. To better cope with the gradient vanishing problem in this very deep network, we introduce speeded up robust features (SURF) which is a patented local feature detector and descriptor. Extensive experiments have been performed on several kinds of medical noise images, such as the computed tomography and ultrasound images, and the proposed method has consistently outperformed stateof-the-art denoising methods.

**Keywords:** Gaussian model, deep iterative downup convolutional neural network, Speeded up robust features, denoising.

## I. INTRODUCTION

The medical noises would obviously increase the uncertainties in the measurement procedures, and degrade the quality of the images seriously, which make them diagnostically unusable. Numerous image denoising methods have been proposed in the past decades. In this work, we define the noise as anything that is not expected to be presented in the medical images. The noises have different appearances in different imaging instruments and can be broadly classified into two categories: the independent random noise and the structurally correlated/fixed pattern noise. Networks using downscaling and up-scaling of feature maps have been studied extensively in low-level vision research owing to efficient GPU memory usage and their capacity to yield large receptive fields.

The noise in the medical image leads to serious problem. There are some of the existing methods to remove the noise in the image, medical imaging and diagnostic techniques [8] have gained immense attraction due to the rapid development in computing, internet, data storage and wireless technology. The reflection of these advancements has become evident in the field of medicine and medical sciences which enables the diagnosis and treatment of various diseases in a more fruitful manner. A method for reducing speckle noise in medical ultrasonic images is presented [6]. It is called the adaptive weighted median filter (AWMF) and is based on the weighted median, which originates from the well- known median filter through the introduction of weight coefficients.

The deep convolutional neural network is used to preserve image edges [9]. The network is trained by using the edge map obtained from the well-known Canny algorithm and aims at determining if a noisy patch in non-subsampled shearlet domain corresponds to the location of an edge. Ultrasound diagnostic techniques are widely used in medical clinical diagnostics. However, the presence of speckle noise in the ultrasound imaging process reduces the image quality and creates inconvenience to the physician during clinical diagnosis. despeckling method [14] based on nonsubsampled shearlet transformation and a 13 guided filter. With ideal spatial adaptation, an oracle furnishes information about how best to adapt a spatially variable estimator, whether piecewise constant, piecewise polynomial, variable knot spline, or variable bandwidth kernel, to the unknown function [2].

A deep convolutional neural network [1] is trained to transform low-dose CT images towards normal-dose CT images, patch by patch. Based on the compressed sensing theory [13], if an object under reconstruction is essentially piecewise constant, a local ROI can be exactly and stably reconstructed via the total variation minimization. a deep iterative down-up convolutional neural network (DIDN) [12] for image denoising, which repeatedly decreases and increases the resolution of the feature maps. reduction of Gaussian noise of Computed Tomography (CT) image and Rician noise of Magnetic Resonance Imaging (MRI) image based on a given set of standard images and the [10] Kernel Ridge Regression (KRR). In contrast with the traditional NL-means algorithm [7] , the adaptive NL-means denoising scheme has three unique features.

## II. METHODOLOGY

The model is designed for remove the noise from the image and to reduce the time rate and increase the performance of the process. The input image is fed to the normalization. The Normalization is used to reduce the pixel range of the image. The SURF feature is used for extracting the important features in the image. CNN is used to remove the noise from the image.

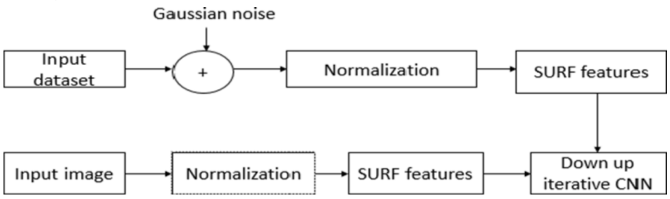


Fig 1 Block Diagram

### A. Speeded Up Robust Feature

The SURF method (Speeded Up Robust Features) is a fast and robust algorithm. The SURF approach lies in its fast computation of operators using box filters.

SURF is composed of two steps

- Feature Extraction
- Feature Description

- Feature Extraction
  - Interest point detection uses a very basic Hessian matrix.

- Integral images:
  - Quick and effective way of calculating the sum of values.
  - Used for calculating the average intensity within a given image.

    $(x, y) \sum \sum I(i,j)\ y\ j=0\ x\ i=0$

    S(x,y) represents the sum of pixels in the input image

- Hessian matrix-based interest points:
- Surf uses the Hessian matrix.
- Instead of using a Hessian-Laplace detector, surf relies on the determinant of the Hessian matrix.
- The Hessian matrix H (x, σ) in x at scale σ is defined as $\mathcal{H}(\mathbf{x},\sigma)=\begin{bmatrix} L_{xx}(\mathbf{x},\sigma) & L_{xy}(\mathbf{x},\sigma) \\ L_{xy}(\mathbf{x},\sigma) & L_{yy}(\mathbf{x},\sigma) \end{bmatrix}$

  where, Lxx (x, σ) is the convolution of the Gaussian second order derivative with the image I in point x

  σ Scale (Standard deviation of Gaussian)

  The determinant of Hessian matrix is represented as

  Det (H approx) = $DxxDyy$- (w$Dxy$) 2 where, w=0.9(Bay's suggestion)
- Feature Description

  The creation of SURF descriptor takes place in two steps.

  Fixing an orientation based on information

  Square region aligned to the selected orientation and extract the SURF descriptor from it.
- Orientation Assignment:

  For achieving Orientation in point of interest,

  Calculate the Haar-wavelet responses in x and y-direction

  Calculate the sum of vertical and horizontal wavelet responses

  V = ($\sum d$ , $\sum dy$ , $\sum|dx|$ , $\sum|dy|$ )

## B. Deep Iterative Downup CNN

The Convolutional Neural Network (CNN) is a class of deep learning neural networks. The basic structure of the network is inspired by U-Net which was originally developed for semantic segmentation. We modify the down-scaling and up-scaling layers for image denoising task.

- Down and Up scaling used in the Contraction and Expansion.
- Contraction reduces the size of feature.
- Expansion increases the size of the feature.

DIDN consists of four parts: feature extraction, down-up block (DUB), reconstruction, and enhancement.

Initial feature extraction: When the size of the input image is H×W, DIDN first extracts $N$ features using a 3×3 convolution on the input image, and extracts the features of $H$ 2 × $W$ 2 × 2$N$ size through the convolution layer using a stride of 2.

**DUB:** The extracted features subjected to iterative downup scaling through several DUBs. In the DUB, contraction and expansion are performed by two down-scaling and upscaling processes. A 3×3 convolution layer with a stride of 2 and a subpixel layer are used in down- and up-scaling, respectively.

**Reconstruction:** A common reconstruction block after the last DUB to take advantage of all the local output. The outputs of all the DUBs form the inputs to the reconstruction block, and all the outputs of the reconstruction block are concatenated to go through the enhancement stage. The reconstruction block consists of nine convolution layers (Conv) followed by parametric rectified linear units (PReLU).

Enhancement: Finally, through the 1×1 convolution, the number of output feature maps in the reconstruction block is decreased, and up- scaling is performed at the subpixel layer to generate the final denoised image.

## III. RESULT AND DISCUSSION

The Medical images like the MRI, CT and X ray images are fed as input image. The "Figshare" database is used. This brain tumor dataset containing 3064 T1-weighted contrast-inhanced images from 233 patients with three kinds of brain tumor: meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices).

| Noise Level | Index | Methods | | | |
|---|---|---|---|---|---|
| | | Wavelet Transform | Curvelet Transform | Fast NLM Filter | Deep Iterative Downup CNN |
| 10 | PSNR | 38.22 | 41.13 | 41.16 | 40.59 |
| | SSIM | 0.9184 | 0.9477 | 0.9502 | 0.9453 |
| 20 | PSNR | 34.79 | 37.84 | 37.97 | 37.91 |
| | SSIM | 0.8659 | 0.9175 | 0.9212 | 0.9219 |
| 30 | PSNR | 32.83 | 35.76 | 36.16 | 37.88 |
| | SSIM | 0.8280 | 0.8896 | 0.9004 | 0.9176 |

TABLE I. COMPARISON WITH OTHER METHODS

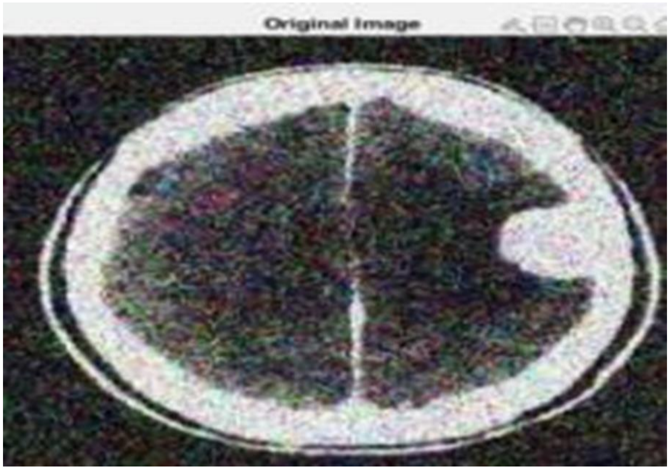


Fig 2 Original image

The Original image is converted into grey scale image.Because the grey scale contains only shades of gray and no color. The grey scale removes all color information , and leave only the luminance of the image.


Fig 3 Grey image

The Normalization is used to change the range of the pixel value.

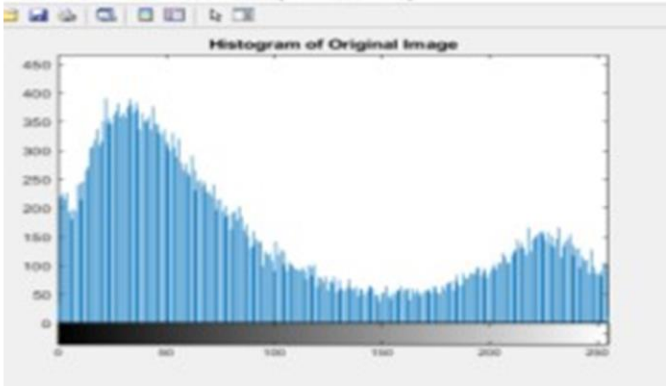


Fig 4 Histogram of image

The SURF features is used to extract the features of the image. By extracting the features of the image the noise can be identified easily.

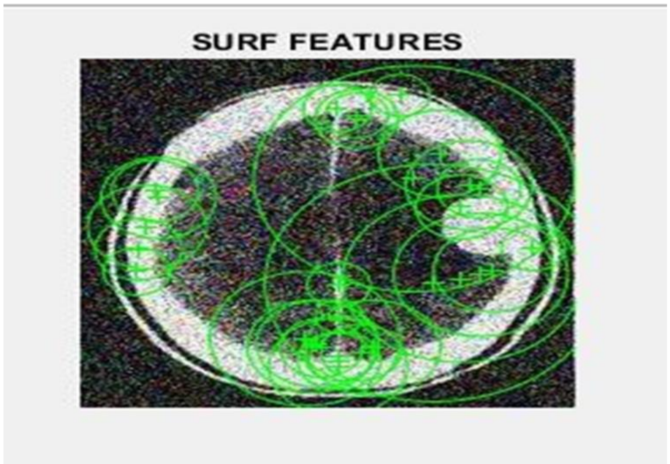


Fig 5 SURF features

The noises in the image are removed by using the downup iterative CNN.

Fig 6 Output

## IV. CONCLUSION

Instead of explicitly modeling the complex distribution of various noises and multi- modality medical images, the deep model could automatically figure out the distribution of the specific noise and image from a data-driven viewpoint. The Up Down CNN model benefits us to handle different noise categories and noise levels adaptively. To facilitate the training, we introduce both the short-term and long-term connections in the network for better information propagation. Moreover, we apply the finetune strategy to alleviate the lack of medical images issue. Extensive simulated and real medical image datasets have been tested.

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