Efficient Denoising Technique for CT images to Enhance Brain Hemorrhage Segmentation

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Abstract This paper presents an adaptive denoising approach aiming to improve the visibility and detectability of hemorrhage from brain computed tomography (CT) images. The suggested approach fuses the images denoised by total variation (TV) method, denoised by curvelet-based method, and edge information extracted from the noise residue of TV method. The edge information is extracted from the noise residue of TV method by processing it through curvelet transform. The visual interpretation shows that the proposed approach not only reduces the staircase effect caused by total variation method but also reduces visual distortion induced by curvelet transform in the homogeneous areas of the CT images. The denoising abilities of the proposed method are further evaluated by segmenting the hemorrhagic brain area using region-growing method. The sensitivity, specificity, Jaccard index, and Dice coefficients were calculated for different noise levels. The comparative results show that the significant improvement has yielded in the brain hemorrhage detection from CT images after denoising it with the proposed approach.

Keywords Curvelet transform · Total variation · Computed tomography

Introduction

Computed tomography (CT) images are widely used in the diagnosis of brain hemorrhage. Brain hemorrhage detection is a primary task from brain CT images for the patients suffering from neurological disturbances and head injury. Brain hemorrhage means the bleeding due to leakage or rupturing of blood vessels within the skull. CT imaging provides experts an extraordinary way to diagnose the brain hemorrhage. It is widely used due to its low cost, widespread availability, short imaging time, and excellent detection of bony details. It is also valuable for patients who are unable to remain motionless during the examination. The visualization of the hemorrhagic clot on brain CT images depends on its properties like density, volume, location, and relationship to surrounding structures [1]. CT scanning of head has some drawbacks such as radiation burden, low contrast, and artifacts due to beam hardening and noise. In spite of all these limitations, CT continues to be one of the main diagnosis tools of head pathology.

Study shows that the noise on CT images is found to be additive Gaussian [2, 3] and even the experts with good amount of experience may not be able to draw correct and useful information from the images. Therefore, this noise should be filtered out without losing important features of the image. Initial efforts in the area of denoising were made by Lee [4] with the ideas based on statistical linear filtering in spatial domain. Linear filters tend to impose blurring effects to the filtered image. A lot of research has been done to reduce the blurring effects [5]. Currently, two main methods exist for denoising the images. The first one is based on modeling patterns of noise and processing an iterative algorithm and the second one is based on the wavelet coefficients of the image. The approach of modeling pattern of noise has broad appeal since a distribution of model can be

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selected by pattern of noise and the amount of noise can be set as noise parameter. Rudin et al. [6] have introduced a total variation (TV)-based model known as ROF (Rudin, Osher, and Fatemi) model which is capable of smoothing the homogeneous areas. It is an iterative-based-constrained optimization type of algorithm which removes the noise by minimizing the total variation norm of the image with constraint calculated from the noise statistics. Several approaches have been proposed to minimize the total variation of ROF model but most of the TV methods cause the staircase effects and diminish some local features like texture, small details, etc. with noise in the form of residue. However, one method which is proposed by Chambolle [7] and that uses nonlinear projection-based approach to minimize the ROF model is particularly found of interest in the present work.

Wavelet-based methods also make good choice for image denoising [8]. Recently, several methods for denoising of CT images have been reported in the literature. Rabbani et al. [9] proposed noise reduction algorithms that can be used to enhance image quality in various medical imaging modalities such as magnetic resonance imaging and CT. Here, noisy data are first transformed by discrete complex wavelet transform and then a mixture of bivariate Laplacian probability density functions is used for obtaining the clean data in the transformed domain. The maximum a posteriori and the minimum mean-squared error estimators allow reducing the noise. Borsdorf et al. [10] proposed wavelet-based structure-preserving method for noise reduction in CT images that can be used in combination with different reconstruction methods. The approach is based on the assumption that the data can be decomposed into information and temporally uncorrelated noise. Ali et al. [11] have used window based multiwavelet transformation and thresholding for noise reduction of CT images. The technique removes additive white Gaussian noise from the CT images and enhances the quality of the images. The technique consists of three different stages of processing, namely, window-based multiwavelet transformation thresholding, reconstruction, and quality enhancement. However, wavelet is an optimal tool for 1-D signals. For dealing with high-dimensional data, it has serious limitations. Wavelet cannot give better denoising due to poor directional sparsity along the curve. Due to these limitations of wavelet, the theory of multiscale geometric analysis has been developed. Donoho and Duncan [12] have introduced the concept of curvelet transform. Unlike wavelets, curvelets are localized not only in position and scale but also in orientation. This localization provides surprising properties to the curvelet transform and it becomes useful tool for many image processing applications [13, 14]. In 2005, Candes et al. [15] proposed fast discrete curvelet transform (FDCT) which is widely used for image denoising purposes. They have proposed two types of FDCT; the first one is unequipped

fast Fourier transform-based curvelet transform (USFFT_Clet) and the second one is wrapping-based curvelet transform (WRAP_Clet). Two denoising approaches were proposed in curvelet domain. In the first approach, hard thresholding function was used and in another, the concept of cycle spinning is combined with curvelet transform (CS_Clet) [16]. In our previous work [17, 18], we have evaluated the performance of both wavelet- and curvelet-based denoising methods on brain CT images and have observed that the curvelet-based method outperforms the wavelet-based methods not only for noise suppression but also for edge preservation. Curvelet-based denoising methods preserve the edges perfectly, however it also generates some visual distortion and fuzzy edges in the homogeneous region of the image. In the present work, we propose an adaptive noise removal approach for CT images, which fuses the images (1) denoised by TV method, (2) denoised by curvelet-based method, and (3) the edge information extracted from the noise residue of TV method by processing it through curvelet transform. The proposed approach is aiming to improve the visibility and detectability of hemorrhage from brain CT images.

“**Total Variation Based Method**” and “**Curvelet Transform Based Method**” sections present brief description of TV method and curvelet-based denoising methods, respectively, which are used by the proposed method. The methodology of the proposed denoising method is presented in “**The Proposed Fusion Based Algorithm**” section. The material and quality assessment parameters are discussed in “**Material and Evaluation of Proposed Method**” section. “**Experimental Results and Discussions**” section presents the results and related observations and finally the “**Conclusion**” section concludes the paper.

Total Variation-Based Method

The total variation-based image denoising method was introduced by ROF [6]. They proposed a regularization expression as:

$$\min_{f \in X} \frac{\|g - f\|^2}{2\lambda} + J(f) \quad (1)$$

where, g is the given noisy image, f is desired image of size $N \times N$, X is the Euclidean space $R^{N \times N}$, $\lambda > 0$ is a Lagrange multiplier and $\|\cdot\|$ is the Euclidean norm. The functional $J(f)$ is the discrete total variation of f and defined as

$$J(f) = \sum_{1 \leq i, j \leq N} |(\nabla g)_{ij}| \quad (2)$$

Several approaches have been proposed for the minimization of ROF expression. In the present work, we use

projection-based approach proposed by Chambolle [7] who solves Eq. 1 as

$$f = g - \lambda \operatorname{div}(p^k) \quad (3)$$

The iterative method for computing the optimal solution of p^k is given as follows:

$$P_0 = 0$$

and

$$p_{ij}^{k+1} = \frac{P_{ij}^k + \tau [\nabla(\operatorname{div}(p^k) - g/\lambda)]_{ij}}{1 + \tau |\nabla(\operatorname{div}(p^k) - g/\lambda)_{ij}|} \quad (4)$$

where for $\tau \leq \frac{1}{4}$.

From Fig. 1a, b, it is clear that some edge information is lost with the residual of TV method due to iterative nature of method and tuning parameter λ .

Curvelet Transform-Based Method

The curvelets are based on multiscale ridgelets combined with a spatial bandpass filtering operation. These bandpass filters are set so that the curvelet length and width at fine scale obey the scaling rule $\text{width} \approx \text{length}^2$. A two-dimensional wavelet transform is used to isolate the image at different scales and the spatial partitioning is used to break each scale into blocks. Large-size blocks are used to partition the large scale wavelet transform components and small size blocks are used to partition the small scale components. Finally, the ridgelet transform [12] is applied to each block. In this way, the image edges at a certain scale can be represented efficiently by the ridgelet transform because the image edges are almost like straight lines at that scale. Thus, the curvelet transform is an extension of the ridgelet transform to detect curved edges effectively. The curvelet localizes a ridgelet so that a curved edge in an image is represented as a collection of linear segments. The basic process of the digital realization

for curvelet transform consists of the following four stages:

Subband decomposition We define a bank of low pass filter P_0 and band pass filters Δ_s , $s \geq 0$ such that the image f is filtered into sub-bands with à trous algorithm [19, 20]

$$f \mapsto (P_0 f, \Delta_1 f, \Delta_2 f, \dots) \quad (5)$$

Smooth Partitioning Each sub-band is smoothly windowed by multiplying sub-band with the corresponding windowing function W_Q produces the results localized near Q_s as

$$h_Q = W_Q \cdot \Delta_s f, \forall Q \in Q_s \quad (6)$$

where, w_Q is collection of smooth windowing function localized near dyadic squares Q_s

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s} \right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s} \right] \quad (7)$$

Renormalization Each dyadic square is centering to the unit scale

$$g_Q = T_Q^{-1} \cdot h_Q \quad (8)$$

where $(T_Q f)(X_1, X_2) = 2^s f(2^s X_1 - k_1, 2^s X_2 - k_2)$ is the renormalization operator.

Ridgelet analysis The two dimensional ridgelet transform in R^2 can be defined as follows:

For each $a > 0$, each $b \in R$ and each $\theta \in [0, 2\pi]$, the bivariate ridgelet $\psi_{a,b,\theta}: R^2 \rightarrow R^2$ can be defined as

$$\Psi_{a,b,\theta}(x) = a^{1/2} \Psi \left(\frac{x_1 \cos \theta + x_2 \sin \theta - b}{a} \right) \quad (9)$$

where, a is scale parameter, b is location parameter, θ is orientation parameter, and ψ is a wavelet. These ridgelets are constant along lines $x_1 \cos \theta + x_2 \sin \theta = \text{const}$ and are wavelets along orthogonal direction.

Fig. 1 a Noisy CT image, b noise residual of TV method, c edge information extracted from noise residual of TV method

For a given function $f(x_1, x_2)$ ridgelet coefficients can be defined as

$$R_f(a, b, \theta) = \int f(x_1, x_2) \Psi_{(a,b,\theta)}(x_1, x_2) dx_1 dx_2 \quad (10)$$

A simple change in variables shows that the ridgelet coefficients of a function f are given by analysis of Radon transform as

$$R_f(a, b, \theta) = \int R_f(t, \theta) a^{1/2} \Psi\left(\frac{t-b}{a}\right) dt \quad (11)$$

where, R_f is the Radon transform which is defined by

$$R_f(t, \theta) = \int f(x_1, x_2) \delta(x_1 \cos \theta + x_2 \sin \theta - t) dx_1 dx_2 \quad (12)$$

δ is Dirac distribution.

Hence, the ridgelet transform [21] is the application of a 1D wavelet transform to the slices of the Radon transform, where the orientation variable is constant and t is varying. The Radon transform can be obtained by applying the 1D inverse Fourier transform to the 2D Fourier transform restricted to radial lines going through the origin. The block diagram of curvelet transform is shown in Fig. 2.

In curvelet transform domain, two denoising methods were developed [16]; in the first one, the curvelet coefficients

are thresholded with hard thresholding and in the second one, cycle spinning process is applied to noisy image before the application of curvelet transform. Following are the two denoising approaches proposed in curvelet domain

(a) *Curvelet denoising using hard thresholding*

The fundamental principle of hard threshold denoising using curvelet transform is the same with hard threshold denoising using wavelet transform. Since the discrete curvelet transform is not norm preserving, the variance of each curvelet coefficient depends on its index γ . The operator of curvelet transform is defined as T , $g_\gamma^{\text{Clet}} = Tg$ denotes curvelet coefficients of noisy image g , $\hat{g}_\gamma^{\text{Clet}}$ is curvelet coefficients after hard threshold processing, thus denoising function is defined as:

$$\hat{g}_\gamma^{\text{Clet}} = \begin{cases} g_\gamma^{\text{Clet}} & |g_\gamma^{\text{Clet}}| \geq K\sigma\sigma_\gamma \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

where, σ is the noise variance of noisy image, σ_γ^2 is the variance of noise after curvelet transform, k is scale-dependent value. The noise variance σ_γ^2 is calculated from the noisy curvelet coefficients by Monte Carlo simulations as

$$\sigma_\gamma^2 = \sqrt{\frac{\sum_{i=1}^N \sum_{j=1}^N g_\gamma^{\text{Clet}} \cdot g_\gamma^{\text{Clet}*}}{N^2}} \quad (14)$$

Fig. 2 Block diagram of curvelet transform

where $g_{\gamma}^{\text{Clet}*}$ is the complex conjugate of g_{γ}^{Clet} .

This type of hard thresholding denoising technique can be used with both USFFT_Clet and WRAP_Clet. The USFFT_Clet version uses a decimated rectangular grid tilted along the main direction of each curvelet. The WRAP_Clet uses a decimated rectangular grid aligned with the image axes. Wrapping-based transform is faster and more efficient than USFFT_Clet version.

(b) *Curvelet denoising using cycle spinning*

To overcome the problem of false Gibbs phenomenon in case of hard thresholding, the concept of cycle spinning combined with CS_Clet is used for denoising. In this case, first cycle spinning is applied on noisy image within certain range to get a shifted image, which has some phase shift compared with the noisy image. Then curvelet transform is used to obtain curvelet coefficients g_{γ}^{Clet} . Subsequently hard thresholding at finest scale $k=2.5$ and at all scale except finest scale $k=2.2$ is applied to coefficients g_{γ}^{Clet} . After applying inverse curvelet transform, the denoised image is processed by inverse cycle spinning to obtain the denoised image whose phase is the same as the noisy image. This process is repeated by changing shift in the range of circulated shifts. Finally, all the obtained results are averaged to get the final denoised image. Both these methods preserve the edges but at the same time induce some unwanted fuzzy edges and visual distortion in the homogeneous areas of the images.

The Proposed Fusion-Based Algorithm

The proposed approach fuses the images (1) denoised by total variation, (2) denoised by curvelet transform, and (3) edge information. Edge information is extracted back from the noise residual of TV method by processing it through curvelet transform. Noisy CT images contaminated with Gaussian noise as shown in Fig. 1a is first denoised by total variation method and curvelet transform method separately. Then noise residual of TV method as shown in Fig. 1b is further processed with curvelet transform to extract the edge information as shown in Fig. 1c. Finally, the fusion of images denoised by total variation, denoised by curvelet transform and edge information extracted from residual of TV method is carried out as per the proposed fusion method. In the proposed method, stationary wavelet transform (SWT)-based fusion is preferred over discrete wavelet transform (DWT) as DWT is not translation invariant which leads to blocking and aliasing effect in the fused image where as SWT is exactly shift invariant transform [22].

The proposed method is summarized as follows:

1. Denoise the noisy image by total variation (I_{TV}) as well as curvelet transform (I_{Curvelet}) separately.
2. Extraction of edge information (I_{Edge}) by processing noise residual of total variation method with curvelet transform.
3. Application of the SWT to both I_{TV} and I_{Curvelet} separately up to level 2.

Fig. 3 Brain CT Image denoised by different methods. **a** Noisy CT image ($\sigma=20$), **b** TV method, **c** USFFT_Clet, **d** WRAP_Clet, **e** CS_Clet, **f** proposed approach

4. Estimation of the variance (Var_{TV} and $\text{Var}_{\text{Curvelet}}$) at each pixel of the approximation sub-images at level 2 of denoised images I_{TV} and I_{Curvelet} in block of size 3×3 .
5. Evaluation of the variance difference of both the approximation sub-images as:

$$\alpha = \text{Var}_{\text{Curvelet}} - \text{Var}_{\text{TV}} \quad (15)$$

and normalization in the range $[0 \ 1]$. The value of α is used as a weight factor for fusion process.

6. Estimation of the variance Var_{Edge} at each pixel of edge information I_{Edge} in the block of size 3×3 and normalization in the range $[0 \ 1]$. This value is used as weight factor β for edge information I_{Edge} .
7. Fusion process is based on weight factors α and β as adaptively estimated in steps 3 and 4, respectively, and carried out as per the following proposed relationship

$$W_{\text{fuse}} = \beta \cdot I_{\text{Edge}} + \alpha \cdot W_{\text{Curvelet}} + (1 - \alpha) \cdot W_{\text{TV}} \quad (16)$$

I_{Edge}	is the edge information extracted from noise residual of TV method
W_{Curvelet}	is the approximation sub-image of image denoised by Curvelet method at level 2.
W_{TV}	is the approximation sub-image of image denoised by TV method at level 2.
W_{fuse}	is the fused approximation sub-image at level 2.

Li et al. [23] proposed similar type of equation in spatial domain but they used constant value of weight factor independent of type of image. Whereas the present work presents the relationship in transform domain with adaptively estimated weight factors.

8. Fusion of high frequency sub-images at level 2 in horizontal, vertical, and diagonal direction is performed using maximum rule which selects the higher frequency coefficients with maximum absolute values.

Fig. 4 Segmented hemorrhagic region. **a** Manually delineated (expert 1), **b** manually delineated (expert 2), **c** TV method, **d** USFFT_Clet, **e** WRAP_Clet, **f** CS_Clet, **g** proposed approach

Table 1 Quality assessment parameters for hemorrhage detection

Image1	Std. dev.	Assessment parameters	Denoising methods				
			TV	USFFT_Clet	WRAP_Clet	CS_Clet	Proposed
Expert 1	10	Sensitivity	83.33	84.95	83.75	84.66	86.48
		Specificity	99.81	99.56	99.37	99.37	99.64
		Jaccard index	0.8318	0.8457	0.8322	0.8413	0.8509
		Dice coefficient	0.9082	0.9164	0.9084	0.9138	0.9194
	20	Sensitivity	78.66	82.90	83.60	83.73	84.92
		Specificity	99.81	98.73	97.90	99.41	99.73
		Jaccard index	0.7851	0.8186	0.8188	0.8324	0.8462
		Dice coefficient	0.8796	0.9003	0.9004	0.9086	0.9167
	30	Sensitivity	61.20	81.40	81.04	82.66	83.59
		Specificity	99.87	98.74	98.21	99.59	99.94
		Jaccard index	0.6112	0.8039	0.7962	0.8232	0.8240
		Dice coefficient	0.7587	0.8913	0.8865	0.9030	0.9035
Expert 2	10	Sensitivity	80.46	81.93	80.93	81.42	82.69
		Specificity	100.00	99.67	99.64	99.26	99.56
		Jaccard index	0.8046	0.8166	0.8064	0.8082	0.8233
		Dice coefficient	0.8917	0.8990	0.8928	0.8939	0.9031
	20	Sensitivity	75.95	80.04	81.13	81.17	82.68
		Specificity	100.00	98.95	98.57	99.94	100.00
		Jaccard index	0.7595	0.7921	0.7999	0.8113	0.8232
		Dice coefficient	0.8633	0.8840	0.8888	0.8958	0.9030
	30	Sensitivity	59.03	79.33	78.25	79.77	81.45
		Specificity	99.94	99.70	98.46	99.74	100.00
		Jaccard index	0.5900	0.7909	0.7706	0.7956	0.8107
		Dice coefficient	0.7421	0.8832	0.8705	0.8862	0.8955

9. Reconstruction of the image by taking the inverse stationary wavelet transform.

Material and Evaluation of Proposed Method

In general, to evaluate the effectiveness of the denoising methods, quality assessment parameters like PSNR, UQI, and SSIM etc. are used. Here, in the present work, the performance of the proposed denoising approach is evaluated with the aim to obtain better hemorrhage detection from the brain CT images. For the evaluation, the manually delineated hemorrhage boarder by experts on the original brain CT image is taken as the ground truth. The hemorrhage boarder extracted by standard region growing segmentation method from denoised brain CT image is compared with the hemorrhage boarder drawn by the experts. The brain CT images used in this work are acquired from CT scanner manufactured by GE medical systems. The CT images are scanned with field of view 25×25 cm with peak tube voltage 120 kV and tube current 100 mA. Each image was of 512×512 in size, with 3 mm slice thickness and 10 mm inter slice space.

Sensitivity, specificity, Jaccard index, and Dice coefficients are used to evaluate the performance of the hemorrhage detection from the denoised brain CT image. Sensitivity means percentage of hemorrhagic pixels properly included in segmentation results out off all pixels in the segmentation results. Specificity means percentage of hemorrhagic pixels properly excluded from the segmentation results out off all pixels outside of ground truth hemorrhage. These parameters are defined as follows:

$$\% \text{Sensitivity} = \left(\frac{\text{TP}}{\text{TP} + \text{FN}} \right) \times 100 \quad (17)$$

Fig. 5 Noisy CT image ($\sigma=20$)

$$\% \text{Specificity} = \left(\frac{\text{TN}}{\text{TN} + \text{FP}} \right) \times 100 \quad (18)$$

TP or true positive means a pixel appears in both manually segmented ground truth hemorrhage boarder and hemorrhage boarder detected by region growing method. TN or true negative means a pixel absent in both manually segmented hemorrhage boarder and hemorrhage boarder detected by region-growing method. FP or false positive means a pixel absent in manually segmented hemorrhage boarder but it appears in hemorrhage boarder detected by region-growing method. FN or false negative means a pixel appears in manually segmented hemorrhage boarder but it is absent from hemorrhage boarder detected by region growing method [24, 25].

$$\text{Jaccard Index} = \frac{I_{\text{GT}} \cap I_{\text{RG}}}{I_{\text{GT}} \cup I_{\text{RG}}} \quad (19)$$

Fig. 6 Segmented hemorrhagic region. **a** Manually delineated (expert 1), **b** manually delineated (expert 2), **c** TV method, **d** USFFT_Clet, **e** WRAP_Clet, **f** CS_Clet, **g** proposed approach

$$\text{Dice coefficient} = 2 \times \frac{I_{\text{GT}} \cap I_{\text{RG}}}{I_{\text{GT}} + I_{\text{RG}}} \quad (20)$$

where, I_{GT} represents manually segmented ground truth hemorrhage area, I_{RG} represents hemorrhage area detected by region growing method.

Experimental Results and Discussions

In this section, the performance of proposed denoising approach is compared with total variation method and three different curvelet-based methods namely USFFT_Clet, WRAP_Clet, and cycle spinning-based CS_Clet. The performance evaluation is focused to improve the visibility and detectability of hemorrhage from brain CT images. Figure 3 shows the results of all denoising methods on brain CT image contaminated with additive Gaussian noise of standard deviation 20. The visual interpretation from Fig. 3 shows

that the proposed approach not only reduces the staircase effect caused by total variation method but also reduces visual distortion induced by curvelet transform in the homogeneous areas of the CT images.

The performance of the proposed denoising approach is further evaluated with an aim to obtain better hemorrhage detection from brain CT images. Figure 4a, b shows the manually delineated hemorrhage boarder by two experts from original brain CT image which are taken as ground truth. Figures 4c–g show the results of hemorrhage detection using region growing segmentation technique from brain CT image denoised by different methods. Table 1 show quantitative measurements for hemorrhage detection from brain CT images contaminated with Gaussian noise of standard deviation 10, 20, and 30. It can be observed from Fig. 4c–g and Table 1 that the proposed denoising method outperforms all other methods. There is significant improvement not only in visibility but also in the detection of hemorrhage from brain CT images. To further validate the performance of the proposed denoising approach the same subject experts are requested to manually delineate the hemorrhagic region from a CT image as given in Fig. 5. The manually delineated hemorrhagic regions by two experts are

shown in Fig. 6a–b. The CT image is denoised by different methods and results of hemorrhage detection using region growing segmentation technique from images denoised by different methods are shown in Fig. 6c–g. The quantitative measurements for hemorrhage detection from brain CT image given in Fig. 5 are shown in Table 2 which is further an evidence of significant improvements for the hemorrhage detection.

Conclusion

Brain hemorrhage is the least treatable form of stroke and there remains a lack of effective treatment for brain hemorrhage. This paper suggested a denoising approach which not only improves the visibility but also the hemorrhage detection capabilities from brain CT images. The suggested approach utilizes the features of both TV method and curvelet transform-based method. It reduces the staircase effect induced by TV method and visual distortion induced by curvelet transform in the homogeneous region of the image. The improvement in the hemorrhage detection capabilities from brain CT images may be useful in prognosis and

Table 2 Quality assessment parameters for hemorrhage detection

Image2	Std. dev.	Assessment parameters	Denoising methods				
			TV	USFFT_Clet	WRAP_Clet	CS_Clet	Proposed
Expert 1	10	Sensitivity	75.66	75.57	75.63	76.73	77.98
		Specificity	99.88	99.52	100.00	99.94	99.91
		Jaccard index	0.7557	0.7550	0.7563	0.7668	0.7761
		Dice coefficient	0.8609	0.8604	0.8613	0.8680	0.8739
	20	Sensitivity	64.28	71.59	75.37	70.48	75.80
		Specificity	99.97	99.88	100.00	99.58	99.97
		Jaccard index	0.6426	0.7150	0.7437	0.7119	0.7578
		Dice coefficient	0.7824	0.8338	0.8596	0.8248	0.8622
	30	Sensitivity	60.23	65.88	69.78	69.03	70.99
		Specificity	100.00	99.58	99.09	98.98	100.00
		Jaccard index	0.6023	0.6556	0.6906	0.6823	0.7099
		Dice coefficient	0.7518	0.7608	0.7831	0.7778	0.7951
Expert 2	10	Sensitivity	73.26	75.83	77.86	77.36	76.14
		Specificity	100.00	99.93	99.87	99.99	100.00
		Jaccard index	0.7326	0.7362	0.7776	0.7734	0.7645
		Dice coefficient	0.8456	0.8480	0.8749	0.8722	0.8648
	20	Sensitivity	62.16	73.67	73.11	73.30	74.19
		Specificity	99.82	99.63	100.00	99.93	99.97
		Jaccard index	0.6216	0.7583	0.7311	0.7330	0.7417
		Dice coefficient	0.7667	0.8626	0.8446	0.8459	0.8677
	30	Sensitivity	58.21	69.32	68.81	68.53	72.85
		Specificity	99.57	99.78	100.00	99.96	100.00
		Jaccard index	0.5821	0.6932	0.7043	0.6853	0.7285
		Dice coefficient	0.7359	0.8188	0.8429	0.8133	0.8456

treatment trials. The experiments have shown the efficiency and robustness of the method on brain CT images.

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