3D Adaptive Histogram Equalization Method for Medical Volumes

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Abstract: Medical imaging plays a fundamental role in the diagnosis and treatment of several diseases, enabling the visualization of internal organs and tissues for use in clinical procedures. The quality of medical images can be degraded by several factors, such as noise and poor contrast. The application of filtering and contrast enhancement techniques is usually necessary to improve the quality of images, which facilitates the segmentation and classification stages. In this paper, we develop and analyze a novel three-dimensional adaptive histogram equalization method for improving contrast in the context of medical imaging. Several data sets are used to demonstrate the effectiveness of the proposed approach.

1 INTRODUCTION

Several medical imaging modalities (Ahmad et al., 2014; Beutel et al., 2000) have been employed in modern medicine to aid the diagnosis and treatment of diseases, such as digital radiography (DR), magnetic resonance imaging (MRI), endoscopy (ES), ultrasound (US), angiography (AG), mammography (MG), computed tomography (CT) and positron emission tomography (PET). These imaging techniques allow visual representations of internal structures of the body to be constructed, assisting physicians in diagnostic decisions (Nolden et al., 2013; Thammasitboon and Cutrer, 2013).

During the acquisition process, the quality of medical images can be degraded by artifacts, for instance, noise and poor contrast. Techniques of image filtering and contrast enhancement are necessary to compensate such effects in order to improve the image quality.

In the image processing field (Amorim et al., 2013; Amorim et al., 2015; Moraes et al., 2015), several approaches have been developed to attenuate noise while preserving relevant features. Some common noise removal approaches (Gonzalez and Woods, 2002; Parker, 2010; Russ, 2015) include median filter, Weiner filter, Gaussian filter, bilateral filter, among others. Additionally, enhancement techniques (Hummel, 1977; Singh and Bovis, 2005; Stark, 2000) have been employed to emphasize features or characteristics of the image, such that the resulting image has superior quality than the original one.

Histogram equalization (Gonzalez and Woods, 2002; Hummel, 1977) is a very well known technique for enhancing the contrast of an image, whose main goal is to better distribute the pixel intensities based on the probability distribution of the gray levels. By means of this histogram adjustment, regions with poor contrast are enhanced, producing an overall contrast improvement.

As main contribution of our work, we propose and evaluate a variant of the two-dimensional contrast limited adaptive histogram equalization (2D CLAHE) (Zuiderveld, 1994) to improve contrast in medical images. It differs from the original approach in the sense that our method operates directly on the three-dimensional volumes, without requiring the extraction of two-dimensional sections of images.

Several histograms are constructed and modified to redistribute the pixel intensities of the images, significantly improving their local contrast. Experiments are conducted on different medical volumetric data sets to demonstrate the effectiveness of the proposed method.

This paper is organized as follows. Section 2 briefly reviews some relevant concepts and techniques related to the topic under investigation. Section 3 describes the proposed local contrast enhancement method. Section 4 presents and analyzes the experimental results obtained with our method. Section 5 concludes the paper with some final remarks and directions for future work.

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2 BACKGROUND

A common problem that occurs in medical imaging is the generation of images with poor contrast due to a limited exposure range, which affects the correct interpretation of anatomical structures for diagnosis and treatment procedures.

Enhancement techniques (Chen et al., 2014; Gu et al., 2016; Huang et al., 2013; Kim et al., 1998; Saleem et al., 2017; Stark, 2000; Wang et al., 1983) have been developed to adjust the contrast and improve quality of images in order to make their characteristics more suitable for subsequent stages, such as segmentation and classification. Therefore, after the image enhancement process of an image, a certain component becomes more distinguishable from other components and the background.

Several definitions of contrast have been proposed in the literature. Weber contrast (Fechner, 1860) is expressed as:

$$C_W = \frac{I - I_b}{I_b} \tag{1}$$

where I and I_b correspond to the luminance of the objects and the background, respectively.

Michelson contrast (Michelson, 1995) is defined as:

$$C_M = \frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}} \tag{2}$$

where $I_{\min}$ and $I_{\max}$ correspond to the lowest and highest luminance, respectively.

Root mean square (RMS) contrast (Peli, 1990) is defined as the standard deviation of the pixel intensities:

$$C_{RMS} = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (I_{xy} - \bar{I})^2} \tag{3}$$

where I_{xy} are the elements with x and y coordinates of the image with dimensions $M \times N$, whereas $\bar{I}$ is the average intensity of all pixel intensities in the image. The pixel intensities of I are normalized in the range $[0,1]$.

Contrast stretching (Arici et al., 2009; Chang and Wu, 1998; Yang, 2006) is a basic image enhancement technique used to increase the dynamic range of the gray levels present in the image. A low contrast image typically has its pixel intensities concentrated on a narrow range, such that information may be lost.

Linear contrast enhancement techniques expand the original intensity values of the pixels linearly. Three linear contrast enhancement techniques are briefly described as follows. In the minimum-maximum linear contrast stretching, the pixel values are redistributed to a new range of values specified by lower and upper pixel value limits over the image under normalization. For 8-bit gray level images, the lower and upper limits are usually assigned to 0 and 255, respectively. In the percentage linear contrast stretching, the enhancement is similar to the minimum-maximum approach, however, it employs specified minimum and maximum values within a certain percentage of pixels from the mean of the histogram. In a piecewise linear contrast stretching, the range of the image intensity is expanded in selected areas according to linear function.

Nonlinear contrast enhancement techniques apply non-linear transfer functions to redistribute the intensity values of pixels to increase the contrast of an image. Histogram equalization applies a monotonic non-linear mapping to adjust the intensity values of pixel in the image such that the resulting image contains a uniform distribution of intensities. The cumulative probability distribution can be used to equalize the histogram of an image.

The histogram equalization (Abdullah-Al-Wadud et al., 2007; Cheng and Shi, 2004; Gonzalez and Woods, 2002; Pizer et al., 1987; Russ, 2015) is typically a global process in the sense that it applies a function to transform the image based on the intensity level distribution of the entire image. In certain cases, it is desirable to enhance details over small regions of the image, such that the equalization process can be adapted to produce a local enhancement. In adaptive histogram equalization, the image is divided into a number of non-overlapping blocks, such that the histogram equalization mapping is applied locally within each block. In order to remove artifacts due to block boundaries, the pixel intensities are interpolated across the blocks using an interpolating function.

A variant of the adaptive histogram equalization, known as contrast limited adaptive histogram equalization (2D CLAHE), was proposed by Zuiderveld (Zuiderveld, 1994) to avoid noise to be overamplified in homogeneous regions of the image. This approach limits noise amplification by clipping the histogram through a specified value before computing the cumulative distribution function. Instead of discarding the part of the histogram that exceeds the clip limit, it is redistributed uniformly among all histogram bins (Pizer et al., 1987).

3 PROPOSED METHOD

This section describes the main stages that compose the proposed method for locally equalizing the histogram of the medical images. The method operates directly on the three-dimensional volumes, which is an extension of the contrast limited adaptive histogram equalization (2D CLAHE) (Zuiderveld, 1994) to improve contrast in medical images. Figure 1 illustrates the main components of the proposed three-dimensional contrast limited adaptive histogram equalization (3D CLAHE).

Initially, two-dimensional slices are stacked together to form a volume. The volume is then subdivided in blocks with predefined size. The histogram is calculated for each block and part of histogram is cut according to a predefined value. Finally, the blocks are joined and a trilinear interpolation function is applied to remove artifacts that may occur on the boundaries between blocks.

Algorithm 1 describes the main steps of the proposed three-dimensional contrast limited adaptive histogram equalization (3D CLAHE). Function `CDF` denotes the Cumulative Distribution Function, whereas functions `min` and `max` return the minimum and maximum grayscale values in the given image, respectively. H is a vector of histograms, where each position of the vector stores the histogram of a subblock, CS is an auxiliary vector to store the result of `CDF`, and MAP is a vector that maps each grayscale value to a new intensity value after the histogram equalization.

The trilinear interpolation is expressed as

$$\begin{aligned}
&[(MAP_{LUA}[v_i] \times x_inv_coef \times y_inv_coef \times z_inv_coef)+\\
&(MAP_{RUA}[v_i] \times x_coef \times y_inv_coef \times z_inv_coef)+\\
&(MAP_{LBA}[v_i] \times x_inv_coef \times y_coef \times z_inv_coef)+\\
&(MAP_{LUP}[v_i] \times x_inv_coef \times y_inv_coef \times z_coef)+\\
&(MAP_{RUP}[v_i] \times x_coef \times y_inv_coef \times z_coef)+\\
&(MAP_{LBP}[v_i] \times x_inv_coef \times y_coef \times z_coef)+\\
&(MAP_{RBA}[v_i] \times x_coef \times y_coef \times z_inv_coef)+\\
&(MAP_{RBP}[v_i] \times x_coef \times y_coef \times z_coef)]\\
&\quad /(size_x \times size_y \times size_z)
\end{aligned}$$

where MAP_{LUA}, MAP_{RUA}, MAP_{LBA}, MAP_{LUP}, MAP_{RUP}, MAP_{LBP}, MAP_{RBA}, MAP_{RBP} are the maps for the 8 nearest subblocks (Figure 2). x_coef, y_coef, z_coef are the distances from V_i to MAP_{LBA} for x, y and z, respectively. x_inv_coef, y_inv_coef, z_inv_coef is the distance from V_i to MAP_{RUP} for x, y and z, respectively.

To test our contrast enhancement methodology, we employed MRI volumes, which were subdivided into blocks with size of 8×8×8 voxels. Larger block dimensions, such as 16×16×16 voxels, generated much noise and decreased the peak signal noise ratio (PSNR) values.

The histogram clip value used in our methodology was assigned to 5, since larger values also increased the noise level in the image, consequently decreasing the PSNR value.

Algorithm 1: Proposed 3D CLAHE method.

3D_CLAHE *(image, size, clip_limit, nbins)*
- **input :** image: volumetric image;
  - size: size of subblocks;
  - clip_limit: value at which the histogram is clipped;
  - nbins: number of bins for histogram;
- **output:** image_equalized;
- Divide image into subblocks with the given size;
- Create image_equalized with same size as image;
- **for** *each subblock S_i* **do**
  - H[S_i] ← histogram(S_i, nbins);
  - Clip H[S_i] according to clip_limit and redistribute equally the excess voxels across the histogram;
  - CS ← CDF(H[S_i]);
  - MAP[S_i] ← CS × (max(image) - min(image)) + min(image);
- **for** *each voxel V_i from image* **do**
  - Find 8 closest neighboring subblocks centers;
  - Use the pixel intensity to find the map value at the 8 subblocks;
  - Use the 8 mapped values to interpolate with trilinear interpolation to obtain the V_i mapped value and assign this value to the corresponding voxel in image_equalized;
- **return** image_equalized;

4 EXPERIMENTAL RESULTS

Experiments were conducted on a set of five volumes acquired through magnetic resonance imaging (MRI). These images were extracted from the publicly available OASIS dataset (Marcus et al., 2007).

Magnetic resonance imaging was chosen since this modality commonly generates images with heterogeneous contrast when compared to computed tomography (CT). Each volume contains 256 slices at a resolution of 128×256 pixels.

We compared the proposed method (3D CLAHE) against 2D CLAHE (Zuiderveld, 1994). For 2D CLAHE, the equalization was applied to each slice of the volume using blocks with 8 × 8 pixels. For 3D

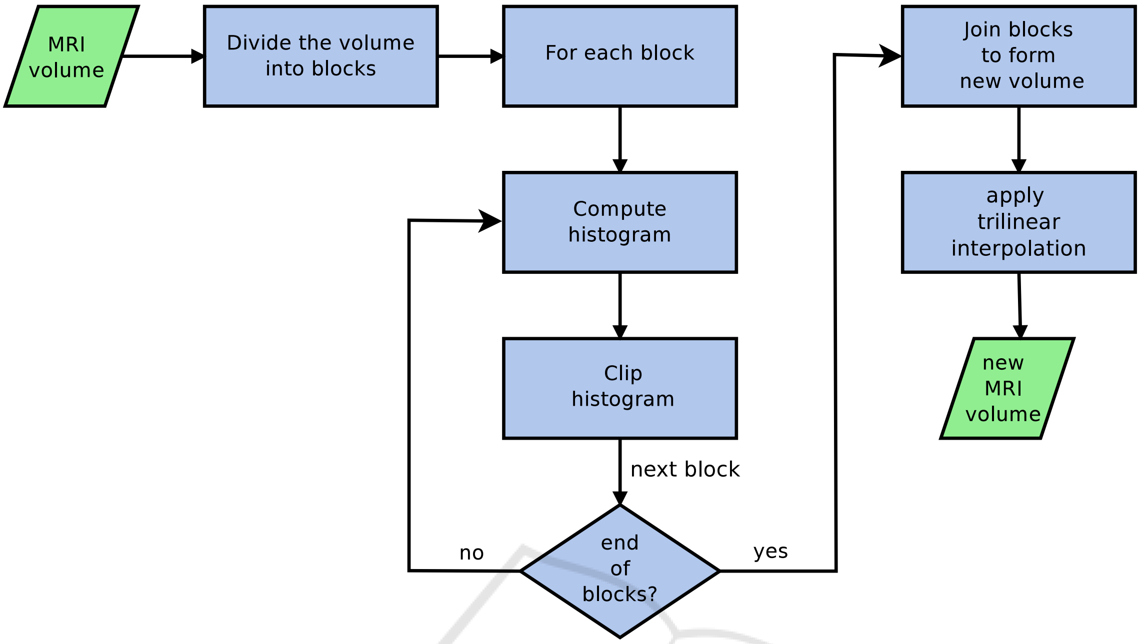


Figure 1: Proposed methodology for three-dimensional contrast limited adaptive histogram equalization.

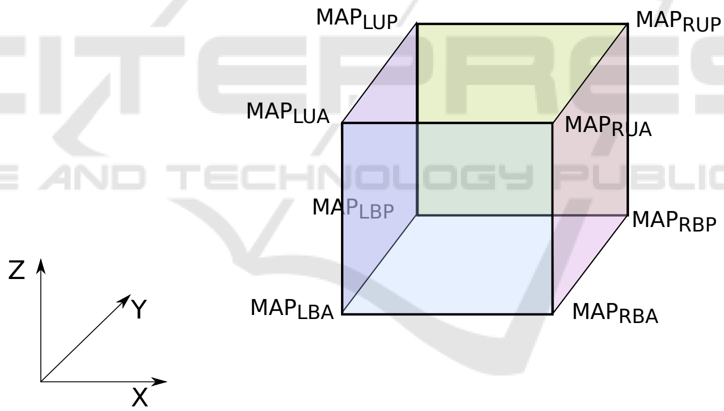


Figure 2: Centers of the 8 subblocks form a cube, which illustrates the position of the maps used in the interpolation.

CLAHE, we used blocks with $8 \times 8 \times 8$ voxels. A histogram clip limit of 5 was used in both approaches.

In the first row of Figures 3 and 4, all images are non-equalized. It is possible to observe that these images have different level of contrast. Images in the second row were equalized with the 2D CLAHE technique. They present better contrast when compared to their corresponding original images, however, the have different contrast between the slices which it is not ideal for volume rendering or 3D segmentation purpose. Finally, images in the third row of Figures 3 and 4 were equalized with the proposed 3D CLAHE method, which present uniform contrast.

The peak signal noise ratio (PSNR) was measured for both 2D CLAHE and 3D CLAHE methods. It is possible to observe from Table 1 that our method achieved higher values of PSNR for all tested images, which means that they are closer to the original image.

Figure 5 shows the results of volume rendering with raycasting technique for two volumes equalized with 2D CLAHE and with the proposed technique. The details in the surface of the brain are clearly visible when the volumetric data sets are equalized with the proposed method.

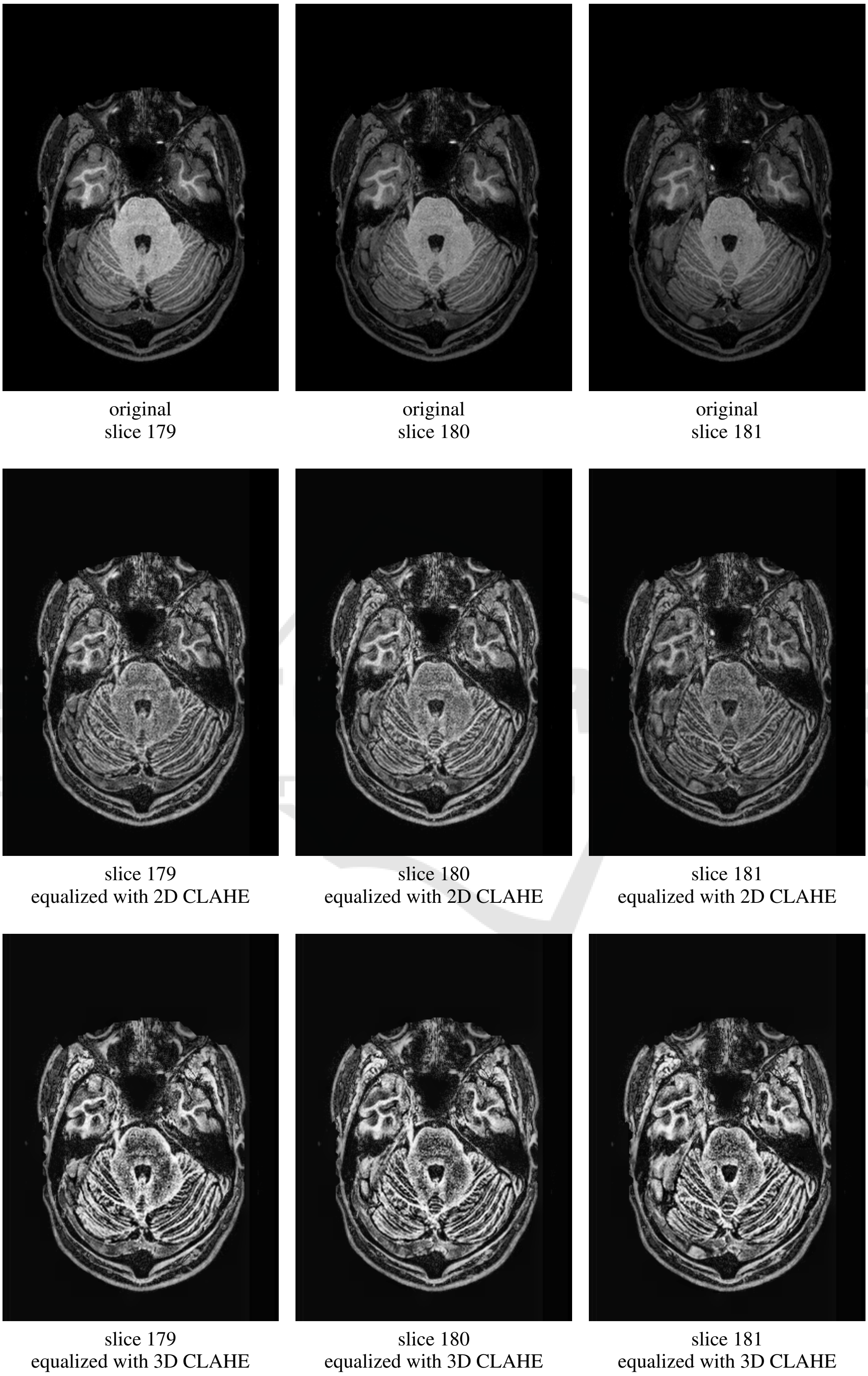


Figure 3: Comparison between input and equalized images with 2D CLAHE and proposed 3D CLAHE method.

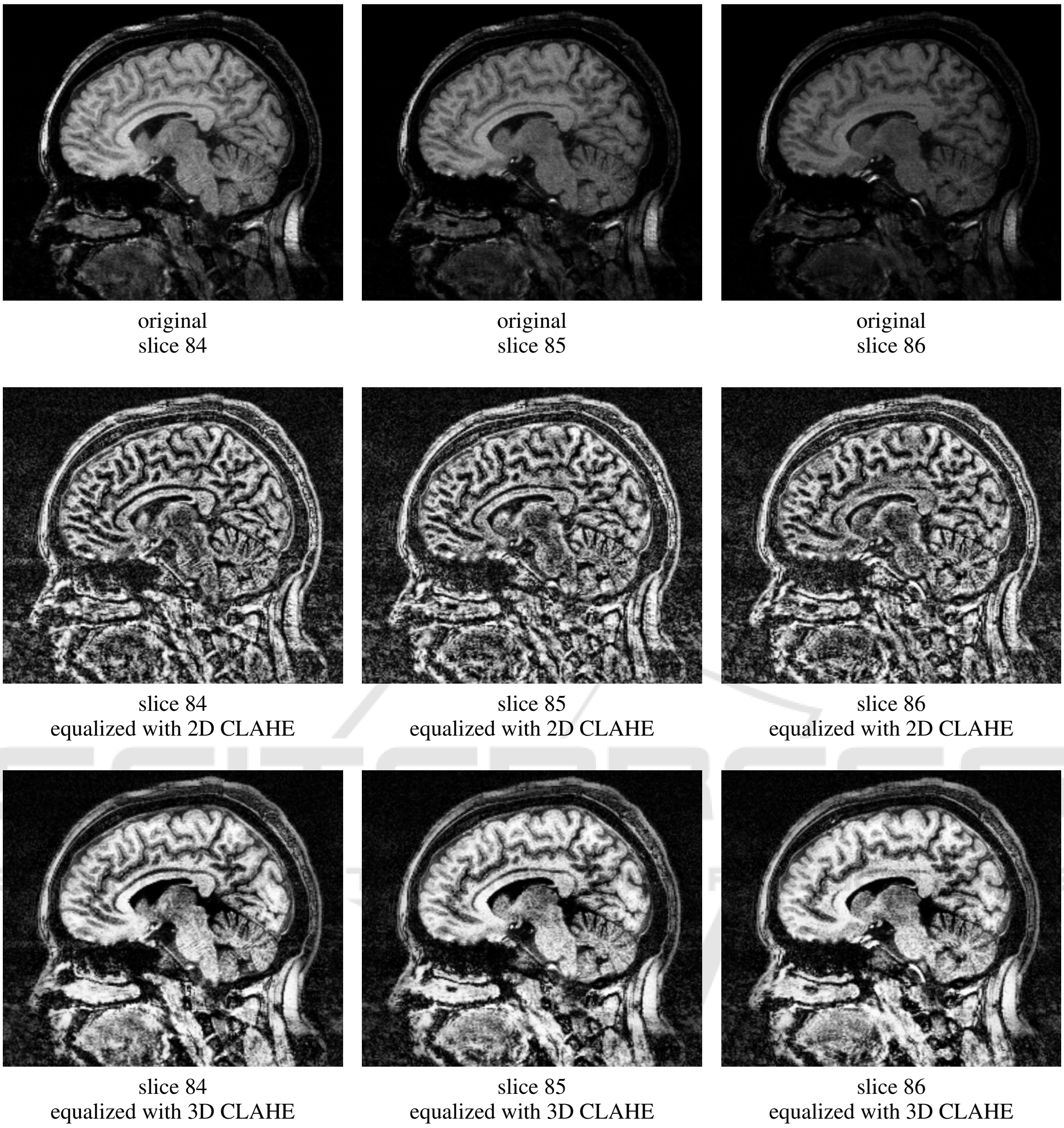
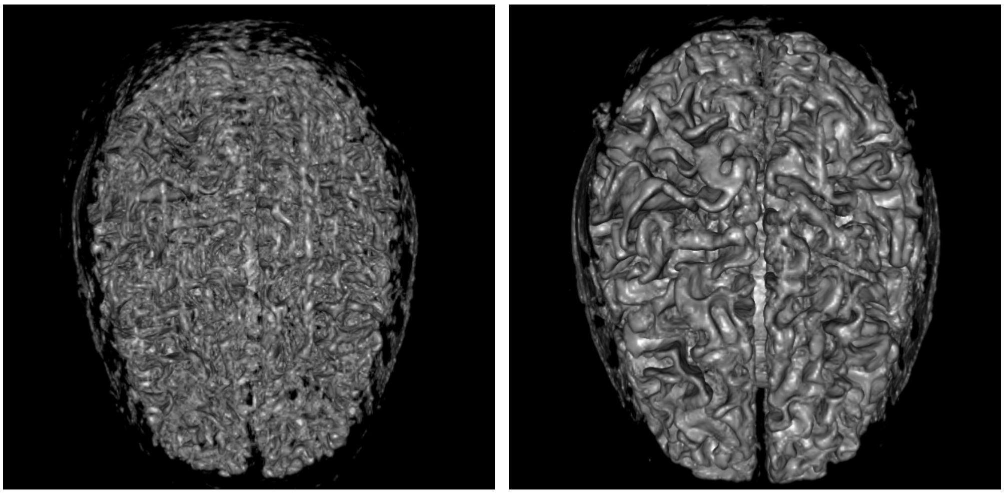


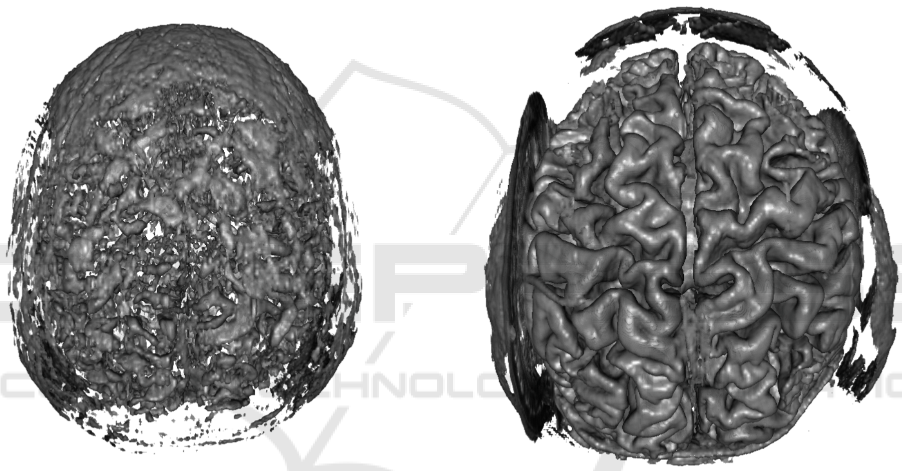
Figure 4: Comparison between input and equalized images with 2D CLAHE and proposed 3D CLAHE method.

Table 1: PSNR values for equalized volumes with 2D CLAHE and proposed method.

Dataset	**PSNR**	
	2D CLAHE	**3D CLAHE**
OAS2_0001_MR1_RAW_mpr-1.nifti.hdr	21.01	73.98
OAS2_0002_MR1_RAW_mpr-1.nifti.hdr	22.24	66.31
OAS2_0003_MR1_RAW_mpr-1.nifti.hdr	18.63	66.86
OAS2_0004_MR1_RAW_mpr-1.nifti.hdr	25.08	68.58
OAS2_0005_MR1_RAW_mpr-1.nifti.hdr	29.01	30.13



equalized with 2D CLAHE — equalized with proposed method



equalized with 2D CLAHE — equalized with proposed method

Figure 5: Comparison between two volumetric data sets equalized with 2D CLAHE and proposed method.

5 CONCLUSIONS AND FUTURE WORK

In this paper, we extended the contrast limited adaptive histogram equalization technique for improving contrast in medical images. Differently from the original method, our method operates directly on the three-dimensional MRI volumes, where the histograms are computed and transformed within blocks extracted from the medical data.

Experiments conducted on a number of medical volumes demonstrated that the proposed method was capable of significantly enhancing the contrast of the images. The resulting volumes can provide health professionals with valuable information for diagnosis and treatment purposes.

As directions for future work, we intend to investigate the extension of other 2D image enhacement techniques to 3D.

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