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Medical Image Colorization for Better Visualization and Segmentation

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Abstract. Medical images contain precious anatomical information for clinical procedures. Improved understanding of medical modality may contribute significantly in arena of medical image analysis. This paper investigates enhancement of monochromatic medical modality into colorized images. Improving the contrast of anatomical structures facilitates precise segmentation. The proposed framework starts with preprocessing to remove noise and improve edge information. Then colour information is embedded to each pixel of a subject image. A resulting image has a potential to portray better anatomical information than a conventional monochromatic image. To evaluate the performance of colorized medical modality, the structural similarity index and the peak signal to noise ratio are computed. Supremacy of proposed colorization is validated by segmentation experiments and compared with greyscale monochromatic images.

Keywords: medical image enhancement, colorization, visualization

1 Introduction

Digital image and signal processing encompasses a vast arena of technologies for analysis of internal biological structure, function and treatment [8]. Medical imaging utilizes fundamental physical phenomena, stretching from acoustic wave dissemination to X-ray propagation, to understand the patient health parameters. Previously medical images represent structural appearance information only, however today they are capable of examining complex and sophisticated internal biological processes such as mutation, metabolism, blood circulation, chemical reactions and many others. Medical imaging is not only contributing in disease diagnoses, but also playing its role in understanding the human anatomy along with evaluation of drugs chemical reaction.

Another versatile contribution of medical imaging is guided surgical assistance during the procedure [3, 26]. There are various studies validating the robotic assisted surgery using medical images [1, 26]. The entire foundation of clinical processes from diagnostic, treatment, surgical procedures and case studies are incomplete without medical images. Machine learning algorithms can provide a strong foundation to build clinical decision support systems using medical imaging [25,29]. Since past few decades, computer-aided detection and diagnosis has emerged as a vibrant research area. Lesions and organs may be diagnosed by examining the biological pattern, thus supporting accurate prognosis and treatment. Medical images hold a precious contribution in visual representation of biological structures and diagnosis of diseases. To embed colour information in traditional medical images play a significant role in clinical decision making. Colourization empowers visual discrimination of biological structures and supports diagnostic decision by surgeons [25].

Computer vision and image processing experts have been contributing in various technologies for decades, whereas colorization is rather new in the medical field. Potentially colorization can play an effective role in medical applications. A number of colorization methodologies, with varying computational costs, have been utilized to colorize greyscale image. A seed of color is used to disseminate color information to similar texture pixels [4]. Colorization technique was initially proposed by Welsh; the technique fell in the category of semi-automatic coloring of natural images. Unfortunately the same methodology generates poor quality colorization for medical images [28]. In the medical domain, technique of false coloring demonstrates induction of coloring in CT (computed tomography) modality images. The short fall of this technique is a consumption of higher system resources during execution [15, 17, 27]. Comparing the luminance intensity among images and colorized MRI (magnetic resonance imaging) images [2].

Image fusion is another approach that has been explored in order to introduce colorized medical images [7, 14]. Using statistical parameters estimation using pervious information with the maximum likelihood criteria the most suitable color may be predicted [19]. In [13] colorized images were generated by cyphering false color code within the image. Texture information was also utilized to predict the similar pattern, potentially propagating colors across the similar texture [16]. Further, video frames were colorized through seeding color in keyframes [9, 12].

2 Literature Survey

Colorization of medical images has been a popular research area for a decade. Identification of effected body cells form grey scale images is challenging as well as time consuming assignment for medical professionals. For assistance of medical experts, colorization of medical images is proposed by image processing specialists for automatic detection of effected parts and better understanding of bio-medical substances. Colorized medical images assist in prevention and treatment of diseases. Colorization techniques can be classified into three types — automatic, semi-automatic and user defined coloring techniques [21].

A seeded colorization scheme is one of recent techniques that propagates color to pixels based on neighbouring pixels. This technique maps colorized scribbles on original gary scale images. Scribbles act as seed and are responsible for describing color of pixels. This technique applies a seeded cellular automaton based on the scribbled method. It was demonstrated that a seeded cellular automaton was able to generates chromatic images from gray scale images with acceptable visual quality [4]. Some studies applied coloring techniques based on threshold.

The drawbacks of the approach is that processing time and memory consumption are very high [15].

In another technique brain MRI classification was achieved by applying two independent methods, (i) highlighting the variability of input images, (ii) segmentation for outlining gray images [2]. It was then followed by a colorization technique to create chromatic brain MRI image. It was reported that there was luminance distance of input image and target image. In [12] a colorization technique was applied on videos using a color seed, populating chromatic information to remaining pixels. Colorized frames were then referred to when colorizing the remaining frames.

To measure performances by various algorithms some standardized quality parameters have been tested, such as a measure of enhancement, a similarity index of the structure, peak signals and entropy [20]. A feature set consisting of mean gray values, mode gray values, area fraction, aspect ratio and standard deviation was used to classify medical images for identification of a tumor, where a number of classification algorithms were tested including Naive Bayes, Tree J48, artificial neural network and Lazy-Ibk. It was found that a neural network classifier produced the most accurate results [11].

Furthermore, image segmentation based on a threshold leading to watershed segmentation and morphological operators was proposed to locate tumorous areas [18]. Similarly, a tumor size and a location were detected by segmentation based on texture information through morphological operators and the dual tree wavelet decomposition [22]. Another work designed an algorithm for detecting regions affected by a breast cancer [6]. Initially the image was enhanced through a Gaussian smoothing filter, which was then followed by morphological operations. The resultant image was disintegrated into two scales using the DWT (discrete wavelet transform) and reconstructed to form a binary image. Classification was made using the artificial neural network and the SVM (support vector machine). It was found that SVM using RBF (radial basis function) and linear kernel exhibited the highest accuracy rate.

3 Pre-processing

The proposed framework requires pre-processing where images are enhanced to get finer details by removing noise and applying normalization techniques. Pre-processing magnifies contrast, brightness and structural details of images. It adds in significant visual illustration, generating colorized medical images with the increased overall quality.

Series of steps are performed to pre-process a grey scale medical image. The standard resolution for images is set to 256×256 pixels. Textual content is removed from the image. Noise removal is achieved by implementing a weighted averaging filter. The source image is convolved with a weighted kernel of the size 3×3. A sliding kernel of the size $m \times n$ is centered at (x, y) of the source $Image(x, y)$ where $m, n = 3$.

Suppose that z_j is the pixel under process, where j represents the number of pixels less than 9. R_{xy} stand for the area to calculate the average of the source $Image(x, y)$. Smoothing of $Image(x, y)$ is achieved by

$$\text{Weighted Kernel} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & +2 & -1 \\ -1 & -1 & -1 \end{bmatrix} \tag{1}$$

Noise is removed from the source and further processed to fix the contrast ratio accentuating the details of image. After completing the noise removal step the contrast is enhanced to highlight the minor details of the image.

The transform intensity $I(x, y)$ is the sum of fraction of the pixel under process z_i and the total number of pixels:

$$I(x, y) = \sum_{i=0}^{n} \frac{z_i}{\text{Total Pixels}} \tag{2}$$

The image is passed to the edge enhancement phase after the contrast improvement. Edge enhancement is done using the Sobel edge detector. The Sobel kernel find the gradient in the vertical and the horizontal direction of the image. The gradients are used to find the magnitude and the direction of edges. Mathematical expressions of the Sobel kernel and operations are presented below. The horizontal and the vertical derivatives $Kernel_x$, $Kernel_y$ are given by

$$Kernel_x = \begin{vmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{vmatrix}, \quad Kernel_y = \begin{vmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{vmatrix} \tag{3}$$

Information is enhanced across edges by adding and subtracting these derivatives near the edges. Convolution $*$ is calculated with the source image:

$$Image_x = Kernel_x * Image(x, y), \quad Image_y = Kernel_y * Image(x, y) \tag{4}$$

resulting in two images with the horizontal and vertical derivative approximations. They are used to calculate the gradient magnitude:

$$Image'(x, y) = \sqrt{Image_x^2 + Image_y^2} \tag{5}$$

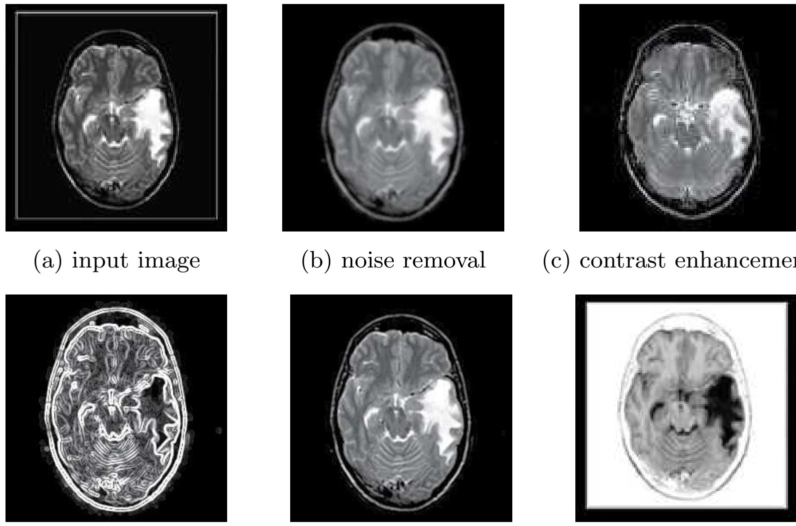
and the gradient's direction:

$$\theta = tan^{-1} \frac{Image_y}{Image_x} \tag{6}$$

The resultant image is more informative than the input because the edge intensity has been increased noticeably. The image is processed further using the negative transformation. Suppose that the maximum intensity of the image is M. The negative of the image is

$$Image''(x, y) = M - Image'(x, y) \tag{7}$$

After the enhancement steps the image is used as an input for the colorization phase. The outcomes of each phase are presented in Fig. 1.



(a) input image (b) noise removal (c) contrast enhancement

(d) edge enhancement (e) image sharpening (f) negative image

Fig. 1: Outputs at pre-processing phases.

4 Colorization

Colorization phase requires a pre-processed image and a chromatic image of to generate a colorized target image of the size 256×256 pixels. The output needs to be three dimensional to hold chromatic information, hence the second and the third channels are populated to the input image.

Normalization is implemented with the input image, leading to the pixel intensity in accordance with the target image. This allows the intensity of the input image to be confined within the defined range. A normalized pixel intensity value is expressed by

$$\text{Normalized value of pixel} = \frac{I(x, y) \times 255}{255 - (L - P)} \tag{8}$$

where L and P are the maximum and minimum values of the intensity.

The source and the target images are both converted to YCbCr color. A comparison of pixel values between two images is computed at Y channel of YCbCr. All pixels from the source image are mapped to chromatic values using chromatic information of the target image. After successful assignment of chromatic information, the source image is converted to RGB colors for better visualization and understanding. Fig. 2 presents the full flow chart of the algorithm.

5 Segmentation

The colorized medical image is segmented to regions to find the area of interest. Segmentation is an important step to identify images that are more relevant.

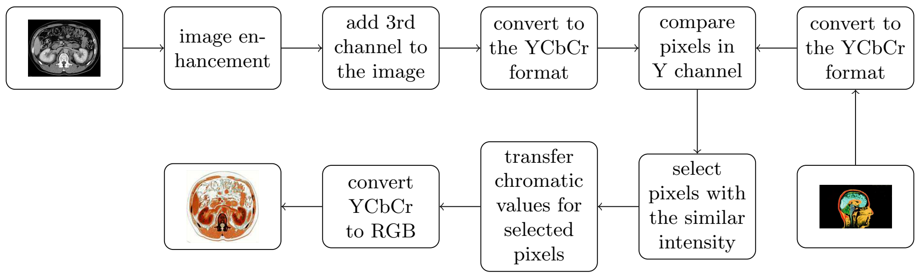


Fig. 2: Flow chart of the proposed algorithm.

After segmentation the image becomes a collection of segments that canvas the entire image. Neighboring pixels are similar in terms of the color, the texture and the intensity.

In the experiment, a PCNN (pulse coupled neural network) and a thresholding are used for segmentation of colorized medical images. A PCNN is used for elicitation of edge information, noise removal and segmentation by analyzing the region of interest. Raw estimation of locating the interested region and background is achieved by key point distribution. A PCNN is able to separate the front end from background. Pixels are processed line by line, starting from left to right or from top to bottom.

6 Result and Evaluation

The approach was tested using several medical image datasets acquired from open source online repositories. Table 1 summarizes their modality and the source.

imaging modality	source
1. CT	images of normal heart, brain and kidney [23]
2. Mammogram	mammography images of above 60 year old women [5]
3. MRI	normal brain, spine and knee images [**?**]
4. Nuclear Medicine	full body, spine and knee images [10]
5. PET	PET images of abdomen, heart and brain [23]
6. Ultrasound	liver images of healthy people [23]
7. X-Ray	X-ray images [24]

Table 1: Datasets for the experiment

6.1 Result

The outcome of the experiment presents better visual description of the image. The proposed algorithm has resulted in meaningful perception of images, where different parts such as tissues, muscles and bones were visualized separately. Table 2 compares the input grey scale images and their colorized images.

6.2 Comprehensive Comparison with the State-of-the-art Techniques

The approach is compared with the recent state-of-the-art techniques [9, 13, 16, 19, 28]. Fig. 3 presents the comparison chart using the PSNR (peak signal-to-noise ratio). It is clearly observed that approach performed far better than other algorithms. The major factor for the significant improvement is caused by image enhancement prior to colorization.

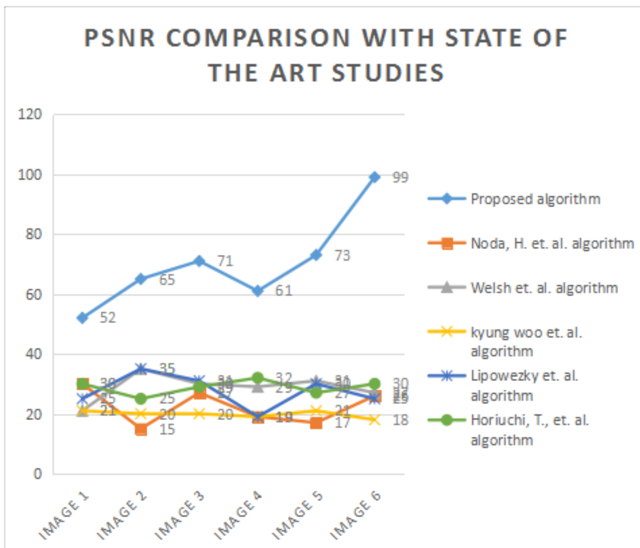


Fig. 3: Comparison chart with the state-of-the-art techniques.

7 Conclusion

Visual information is an important factor for doctors to analyze and diagnose diseases. The proposed algorithm can offer better visualization by clearly differentiating muscle, tissue and the bones area. The advantage of the algorithm is that the structure of an image remain the same during the entire process. Future work may include automatic detection of the disease area based on colored images to support professionals.

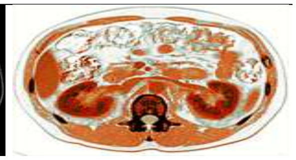
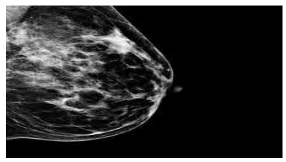
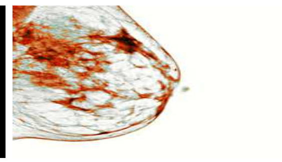
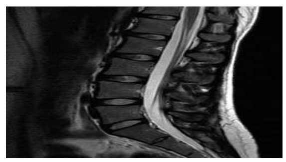
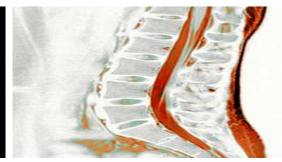
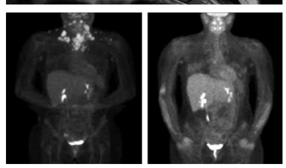
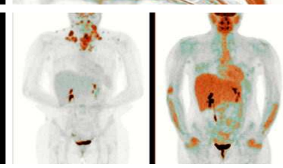
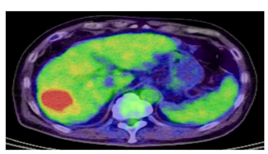
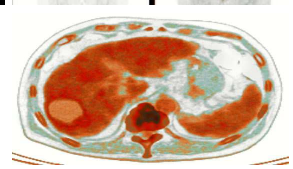
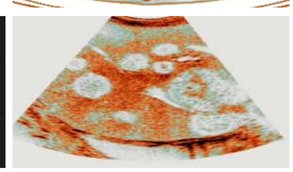
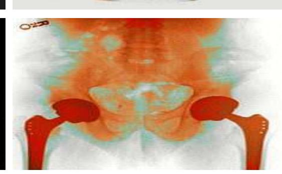
imaging modality	input image	output image
1. CT		
2. Mammogram		
3. MRI		
4. Nuclear Medcine		
5. PET		
6. Ultrasound		
7. X-Ray		

Table 2: Input images and their colarization.

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