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Contrast Enhancement: Cross-modal Learning Approach for Medical Images

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Abstract

Contrast is an imperative perceptible attribute embodying the image quality. In medical images, the poor quality, specifically low contrast inhibits precise interpretation of the image. Contrast enhancement is, therefore, applied not merely to improve the visual quality of images but also enabling them to facilitate further processing tasks. In this paper, we propose a contrast enhancement approach based on cross-modal learning using two-way Generative Adversarial Network (GAN), where U-Net augmented with global features acts as a generator. Besides, individual batch normalization has been used to make generators adapt specifically to their input distributions. The proposed method learns the global contrast characteristics of T1-w brain magnetic resonance images (MRI) to improve the contrast of T2-w images. The experiments were conducted on a publicly available IXI dataset. Comparison with recent CE methods and quantitative assessment using two prevalent metrics FSIM and BRISQUE validate the superior performance of the proposed method.

Introduction

Different degradations are introduced during the image acquisition phase that reduces the lucidity of important details and ultimately affect the extraction of valuable information [31, 15]. Contrast Enhancement (CE) is a primary operation that allows the digital images to be visually perceptible. In the context of medical images, one of the objectives of CE is to improve the perceptual quality for superior visibility of specific structures [18]. Another objective is to facilitate feature extraction and other subsequent tasks such as detection and segmentation of critical structures [24, 25]. It has been reported that the performance of segmentation and detection in medical images can be augmented by employing effective pre-processing techniques on low-contrast images [20, 30, 17, 4].

It is important to mention that a single medical image does not carry complete structural information of the organ under inspection. Multi-modal image acquisition is therefore becoming a standard clinical practice [21]. It not only endorses the initial diagnosis, moreover, it also provides complementary information that can play an influential role in several stages of diagnosis and treatment. The multi-modal image information has been utilized to solve various problems in medical imaging such as segmentation, detection and denoising [29, 7, 19]. The complementary information equips the image analysis tasks with additional capability enabling these methods to outperform those that rely on single images for these tasks [8, 22].

Cross-modal guidance-based enhancement has been applied to natural images [32, 27], where the cross-modality-guided CE methods generally perform well in preventing saturation and over-enhancement phenomena since they exploit the redundant complementary information in the corresponding better quality image [16]. A similar concept was applied to multi-modal medical image enhancement for better visibility of structures [18] and to facilitate tumor segmentation in liver CT images [20].

In this paper, a contrast enhancement method is proposed by learning contrast from corresponding high-contrast medical images of another modality. The multi-modal images employed in this work possess a better perceptual quality that can ameliorate the learning capability of the model. Since image enhancement is a subjective task and it is challenging to acquire the paired ground truth for the supervised learning approaches targeted to contrast enhancement, we formulate the CE problem as an image to image translation problem. The low contrast T2-w brain MR image is transformed into an enhanced image inheriting the contrast of the corresponding T1-w image. A two-way GAN analogous to Cycle-GAN [37] is used for this purpose. The proposed method is inspired by the work of Chen et al. [5] where GAN was used to embed the characteristics of high contrast natural images into low-contrast images under both paired and unpaired data configurations. In this work, the generator is basically a U-Net augmented with global features. The global features carry global contrast information to improve the low-contrast images specifically when acquiring paired ground truth in the form of high contrast images is not feasible.

The paper is structured as follows. First, a review of related work regarding contrast enhancement and GANs is presented. Then, we elaborate on the proposed method followed by experiment results and discussion. The conclusion is drawn in the end of the paper.

Related Work

Contrast enhancement (CE) is one of the most instinctive and commonly applied solutions in medical image applications. There exist several contrast enhancement approaches that improve the perceptual quality of the images, however, the need for controlled CE that does not over-enhance the images is a challenging problem. CE methods can be categorized as spatial or transform domain methods [3]. Among spatial domain approaches, histogram-based methods are widely researched for medical as well as natural image enhancement because of low complexity and reasonable performance [11], [2]. Transform domain methods including wavelet based methods are also widely investigated [26].

Followed by the idea of utilizing the information in a similar

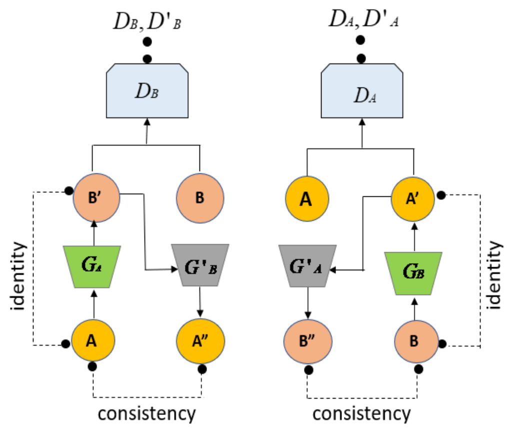


Figure 1: Network Architecture

image to enhance the original image [9], several cross-modality guided image enhancement approaches were proposed for natural images [32, 27]. For instance, Near-infrared (NIR) images were enhanced utilizing photographs [38]. Gradient-based histogram matching along with wavelet domain processing was performed to embed the contrast of NIR images in photos and to enhance texture information respectively. Recently, cross-modal guided enhancement has been extended and applied to medical images as well. A method using 2D histogram specification and morphological operations was employed to map the histogram of liver CT image to that of MR image [18]. In an optimization approach, 2D-HS was combined with structural similarity index metric to retain the structural information in the original image during enhancement [20].

Deep learning methods have been applied to contrast enhancement. These include Convolutional Neural Networks such as the primary work of Yan et al. [33] to adjust the contrast of photograph and another contrast enhancement approach [6] suitable for real-time. Generative Adversarial Networks (GANs) were used by Ignatov et al. [10] to learn the mapping between phone and DSLR cameras. GANs have drawn incredible attention recently and are being applied to solve several difficult tasks including an image to image translation [37], super-resolution [34] enhancement [5, 28] and many other problems.

All the approaches mentioned here require paired training data for network training. Since contrast enhancement is a subjective task, it is generally difficult to collect a huge amount of paired data. Moreover, different users have different preferences for contrast. To address this issue, cycle-GANs were introduced which eradicate the necessity of paired ground truth; instead, the network learns from the unpaired training data by incorporating several loss functions.

The availability of paired training data for medical image contrast enhancement is even challenging and it is difficult to acquire ground truth. However, the redundant complementary information acquired during clinical routine exams makes it possible to enhance the low contrast images using corresponding high perceptual quality multi-modal images. We exploit the capability of two-way GAN in this work to extract global contrast information from the corresponding multi-modal image and embed this information in enhancing the contrast of its corresponding low-contrast medical image. This kind of deep learning based cross-modal CE approach is proposed first time for medical images to the best of our knowledge.

Method

In this section, we discuss our proposed methodology. First, a general description of two-way GAN is provided, then we explain the generator architecture followed by loss functions.

As mentioned earlier, 2-way GAN is particularly suited in scenarios where acquisition of paired input-ground truth data is challenging. Our proposed method discovers and learns global contrast from the label images to embed this information in the generated images. The images enhanced as a result possess those characteristics while simultaneously possessing the content of the input image due to the loss functions used. This kind of framework has shown drastic performance in the image to image translation domain due to its ability to learn the embedding of input data and generating output samples in the space spanned by training samples. This concept has been exploited for natural image enhancement as well, where the two-way GANs were used to learn the mapping between input and ground truth under paired supervision and unpaired supervision. Under unpaired supervision, the high contrast images, as well as HDR images with entirely different content, were used for training. Inspired by this work, we employ the corresponding high contrast multi-modal images as labels for this purpose that share similar objects contours as the input images.

In the proposed method, the source domain and target domain data are denoted by A and B respectively, the source domain consists of low contrast T2-w MR images and the target domain is a collection of high contrast T1-w images. The general configuration of two-way GAN is depicted in the figure 1. Considering $a \in A$, the generator G_A converts a into b', where $b' = G_A(a) \in B$, The discriminator D_B discriminates between real samples (target domain) and generated data (fake samples). 2-way GAN imposes cycle consistency loss, where G'_B accepts G_A-generated sample and applies backward mapping to transform it to source domain A. These GANs employ forward pass and backward pass represented as $a \xrightarrow{G_A} \mathrm{b}' \xrightarrow{G'_B} \mathrm{a}'' and \mathrm{b} \xrightarrow{G_B} a' \xrightarrow{G'_A} b''$ to inspect the consistency between a and a'' as well as b and b'' respectively.

The design of our generator is explained hereinafter. U-Net

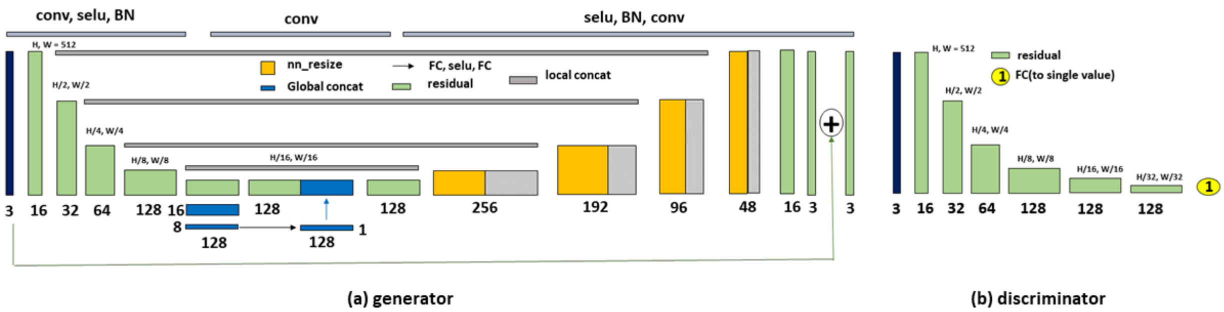


Figure 2: Network Architecture of a) generator and b) discriminator

has been used as generator in our work. Initially applied to medical image segmentation, U-Net has shown promising performance on several imaging problems. However, adapting the original U-Net as our generator cannot guarantee efficient enhancement considering the unpaired data. Therefore, global features have been added into the U-Net, the conjecture is that the global features manipulation works well in learning the global contrast of the corresponding multi-modal data samples. In U-Net, 5×5 filtering (stride 2) is used for every contraction stage, after which SELU activation and batch normalization are applied. Followed by $32\times32\times128$ feature map (fifth layer), the feature map reduces to 16x16x128 and 8x8x128 afterward. A fully connected layer is then used to further reduce the feature map to $1\times1\times128$. These global features are duplicated as 32x32 and concatenated with $32\times32\times128$ feature maps to combine global and local features. U-Net's expansion path then uses combined features. The residual connection is also used in the U-Net so the generator learns the difference between input and label. Figure 2 elaborates the detailed architecture of generator and discriminator.

Several losses used in the method are expressed below. The first that is identity mapping loss I enforces the transformed image b content to be analogous to that of input a:

$$\text{I}= \mathop{\mathbb{E}}_{a,b'}\left[MSE\left(a,b'\right)\right]+\mathop{\mathbb{E}}_{b,a'}\left[\text{MSE}\left(b,a'\right)\right] \tag{1}$$

The consistency loss C can be expressed as:

$$C=\mathop{\mathbb{E}}_{a,a''}\left[MSE\left(a,a''\right)\right]+\mathop{\mathbb{E}}_{b,b''}\left[MSE\left(b,b''\right)\right] \tag{2}$$

The adversarial losses A_D and A_G are expressed as:

$$A_D=\mathop{\mathbb{E}}_{a}\left[D_A(a)\right]-\mathop{\mathbb{E}}_{a'}\left[D_A\left(a'\right)\right]+\mathop{\mathbb{E}}_{b}\left[D_B(b)\right]-\mathop{\mathbb{E}}_{b'}\left[D_B\left(b'\right)\right] \tag{3}$$

$$A_G=\mathop{\mathbb{E}}_{a'}\left[D_A(a')\right]+\mathop{\mathbb{E}}_{y'}\left[D_B\left(b'\right)\right] \tag{4}$$

The gradient penalty P is incorporated while training discriminator:

$$P=\mathop{\mathbb{E}}_{\hat{a}}\left[\max\left(0,\|\nabla_{\hat{a}}D_A(\hat{a})\|_2-1\right)\right]+\mathop{\mathbb{E}}_{\hat{b}}\left[\max\left(0,\left\|\nabla_{\hat{b}}D_B(\hat{b})\right\|_2-1\right)\right] \tag{5}$$

The expression guarantees 1-Lipschitz constraint for Wasserstein distance. Therefore, discriminator is attained by doing optimization as follows:

$$\arg\max_{D}\left[A_D-\tilde{\lambda}P\right] \tag{6}$$

$\tilde{\lambda}$ is adjusted using adaptive Wasserstein GAN (A-WGAN). Generator is obtained by doing the following optimization:

$$\arg\min_{G}\left[-A_G+\alpha I+10\alpha C\right] \tag{7}$$

α determines weight between adversarial and identity/ consistency loss. Conventionally, 2-way GANs employ the same generator for G_A and G'_A since both transform the input samples in domain A to domain B (the same applies to G_B and G'_B). However, G_A accepts input from the original distribution (real samples) whereas G'_A accepts the generated (or fake) samples; both possess different distributions. Enabling the two to specifically adapt to their inputs results in higher PSNR in enhancement problems [5], therefore, individual batch normalization (iBN) layers were used for G_A and G'_A. Except for BN layers, the rest of the layers and parameters are shared between the two.

Experiment

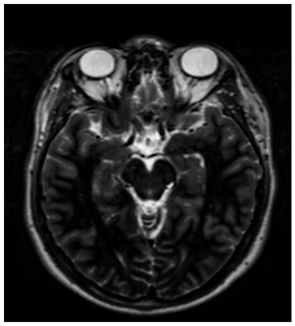
This section explains the dataset used for the experiment, pre-processing applied to data, and the methods selected for comparison.

Dataset

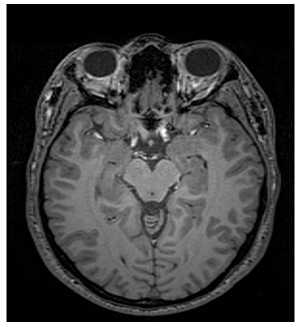
The public dataset of Hammersmith Hospital, United Kingdom accessible on the IXI database [12] was used for analyzing the performance of the proposed method in comparison with other enhancement approaches. Total 3000 image pairs (T1-w, T2-w) were used for training, whereas 400 were used for testing. Input to our network (T2-w images) was darkened by applying morphological operations, whereas original T1-w images were used as reference or label images.

Implementation Details

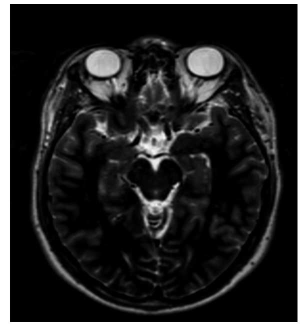
The proposed method is implemented in PyTorch. The network was trained for 100 epochs with the learning rate 1e-5. Weight decay values was 0.5. All the images were 512×512. The network was trained on RTX Twin Titan with a batch size of 8.



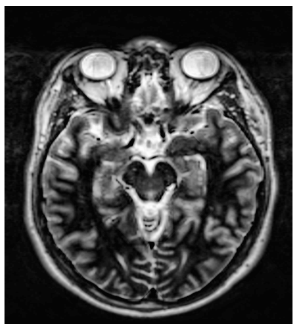
(a1) Input



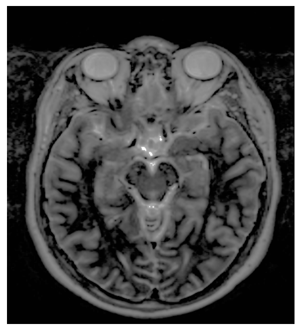
(a2) Label



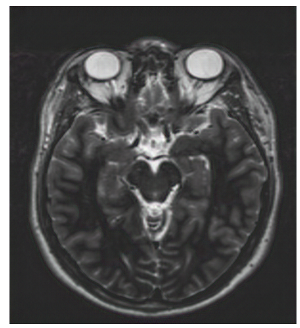
(a3) Zohair et al. [1]



(a4) CLAHE [39]



(a5) CMGE [18]



(a6) proposed

Figure 3: Enhancement Results: Comparison with recent methods

Experiment Results

The proposed method was compared with three contrast enhancement methods. The first method, Contrast Limited Adaptive Histogram Equalization (CLAHE) [39] is one of the well-known and widely accepted methods for CE. Cross-modality Guided Enhancement (CMGE) was proposed recently to improve the contrast of medical images using cross-modal guidance information in a 2D histogram-based approach [18]. The third method is a modification of single-scale retinex with the inclusion of sigmoid function presented for low contrast medical images [1]. The enhancement results from all the methods are shown in figure 3. The input image is a low-contrast dark T2-w brain MR image. The method proposed by Zohair et al. [1] further darkens the image. CLAHE on the other hand improves the contrast; CMGE also improves image contrast in some regions, however qualitative analysis shows the over-enhancement phenomena in case of both the enhanced images. The proposed method improves the contrast without over-enhancing certain areas of the image. The quantitative assessment done to compare all the approaches is discussed below.

Image Quality Assessment (IQA) metrics Feature Similarity Index Metric (FSIM) [35] and Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) [36] are well accepted for the evaluation of medical images in addition to natural images [13, 14, 23]. FSIM is a full-reference IQA metric whereas BRISQUE is a reference-less metric. Both were used to evaluate the performance of the enhancement methods considered in this work. Table 1 presents the results of the quantitative assessment. It is important to mention that higher FSIM scores while lower BRISQUE scores imply superior contrast. Considering the quantitative results, we observe that the proposed method works best in preserving the important features in the enhanced image as shown by the highest FSIM values. Besides, it also prevents the artifacts in the enhanced images as pointed by the BRISQUE results.

Table 1: Quantitative Assessment

Metric	Zohair et al. [1]	CLAHE [39]	CMGE [39]	Proposed
FSIM	0.812	0.714	0.715	0.984
BRISQUE	47.132	45.172	52.582	32.838

Discussion and Conclusion

A cross-modal learning approach for contrast enhancement of medical images is proposed in this paper. The capability of 2-way GAN coupled with global features in U-Net bypasses the need for paired ground truth. Instead, the complementary information and structural similarity of redundant multi-modal medical images has been exploited and effectively utilized in the learning framework. The proposed method improves reasonable contrast without introducing artifacts. The experimental results on the publicly available dataset prove that the method not only retains the features but also maintains the structure and naturalness of the original T2-w MR images as evaluated by the quality assessment metrics. This concept can be further extended to other multi-modal medical images including Computed Tomography and Positron Emission Tomography images.

Author Biography

Rabia Naseem and Faouzi Alaya Cheikh are affiliated with the Norwegian University of Science and Technology, Gjøvik, Norway. Rabia Naseem is a Ph.D. candidate, and Faouzi A. Cheikh is a Professor. Akib Jayed Islam is a master's student under the Erasmus+ Joint Master Program in Computational Colour and Spectral Imaging (COSI). Azeddine Beghdadi is a Professor at University Sorbonne Paris Nord, France.

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