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Metal Artifacts Reduction in Dental CT Scans

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Abstract
Artifacts (noise) caused by the presence of metals in computed tomography scans, impact their readability and can cause problems when making decisions for medical professionals. In recent years, deep learning-based methods have seen considerable success in solving this problem, compared to older hand-crafted solutions. In this work, a supervised neural network model is proposed, along with a better way to solve the problem of creating a synthetic dataset, as otherwise it is naturally impossible to obtain. The results in evaluation metrics achieved are on par with those of state-of-the-art solutions while reducing the need for prerequisites that are complicated to prepare. This generalized solution enables a broader and easier application without needing a specific controlled environment.

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1. Introduction

One of the most important parts of clinical diagnosis and treatment planning are computed tomography (CT) images, where artifacts (noise) caused by the presence of metals could negatively impact decision making for medical professionals. Thus, the problem of metal artifact reduction (MAR) needs people's attention.

Metals, unlike body tissues, significantly attenuate X-rays in a nonuniform fashion over the spectrum, which causes streaking and shading artifacts. The MAR problem can be attempted in two ways, either removing artifacts together with metals or just trying to remove the artifacts while keeping the metals in, the latter being our preferred one.

This problem has been addressed in various ways, ranging from hand-crafted solutions [1, 2] to different approaches based on deep learning [3, 4, 5, 6]. Generally, these solutions can be grouped into three categories, namely, image enhancement, sinogram enhancement, and dual enhancement (joint image and sinogram). Each of these approaches has its own benefits and drawbacks. Lately, deep learning-based dual enhancement such as InDuDoNet [6] has seen the best results and can be considered state-of-the-art.

The common thing across a number of works in different ways and categories is to have an estimated value (threshold) and use that to create a metal trace sinogram, i.e., sinogram of only the metals present. This work attempts to tackle this problem without using any estimates, since our dataset is composed of CT images from all kinds of scanners and different metals [7].

We were able to achieve results comparable to current state-of-the-art methods, while keeping the complexity to a minimum, while using a solution that does not rely on predefined estimates, and also create a more realistic synthetic dataset.

2. Synthetic Generated Dataset

As stated before, images with and without artifacts of the same patient are practically unobtainable, due to the fact that they would require scanning the patient before and after medical intervention. Pulling out patients metal implants and putting them under another radiation exposure obviously isn't realistic. In most similar works [3, 6] a simple way of creating metal masks and selecting metal-free images, which are then most often combined randomly, is adopted. This can lead to combinations that do not represent real-world examples. We adopt a different way of generating a synthetic dataset that should lead to increased similarity of the synthetic data to the real data.

This being one that requires CT scans along with segmented teeth out of them and produces a pair of images with implanted metals and with or without artifacts Fig. 3. At the locations of the randomly chosen teeth, there are 3 types of metal implants generated according to the shape and size of the chosen tooth, which are fillings, crowns, and root canals. In this way, we can ensure that the metals actually sit in a place that makes sense in the CT scans.

3. Network Architecture

For our neural network, we wanted to keep the inputs (prerequisite data) to a minimum, and so our architecture ended up with having just 1 input, that being the metal affected image, and it outputs an image with reduced artifacts. The problem itself is very similar to denoising or demosaicking and that is often tackled with a convolutional neural network. First, a simple convolutional auto-encoder-like architecture was tried. The results achieved with that were surprisingly solid for such a simple network. After a few iterations, we tried a similar U-net-like [8] architecture as depicted in Fig. 4, that adds some residuality in the form of skip connections, which helps us preserve the metals and a sharper output.

Our neural network model was also trained by a novel loss function that combines the mean absolute error, otherwise known as the ℓ_1 error, and the multiscale structural similarity index (MS-SSIM [9]), as this should be the best option for image restoration tasks [10].

4. Results

For measuring our performance, we chose two popular image quality assessment metrics, the peak-signal-to-noise ratio (PSNR), and the structural similarity index measure (SSIM). Using these metrics, we can quantitatively measure the similarity of our input and ground-truth images.

The performance in our synthetic data set can be seen in Fig. 5, where we were able to achieve a near perfect SSIM (identical images result in SSIM of 1) and a high PSNR in which the higher the value, the better.

These results alone are not enough to reasonably qualify our performance, so we compare them with the state-of-the-art InDuDoNet. As we were unable to adapt our dataset to InDuDoNet requirements, we measured the performance of our architecture on a publicly available subset of their dataset. This comparison is not the most appropriate, but it depicts the complicated requirements of other methods compared to ours. This dataset was made up of CT scans with different metal shapes and different body parts (lung and hip CT scans) than ours. And after being re-trained on completely different data for only about 1000 iterations, we obtained competitive results to their presented performance.

As quantitative results alone might not portray the actual performance and quality of the output, it is also good to look at the visual results in Fig. 6. The results are displayed for the primary focus of this work, the 2D dimension (slices), and also for the whole scans, where each slice is cleaned separately and then put back together. In both results, we can see that the artifacts are quite heavily suppressed, but in the process of doing so, we lose some clarity and sharpness of the image.

5. Conclusions

Our proposed method was able to achieve near state-of-the-art results while lowering the barrier to entry (amount of prerequisites). However, we also acknowledge the room for improvement in terms of sharpness and clarity of the output images. In the future trying to add more residuality to our network might prove useful, and we would also like to experiment with the newly emerging state-of-the-art in computer vision stable diffusion models, which haven't been tried for this problem yet.

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