Medical Image Inpainting Using Multi-Scale Patches and Neural Networks Concepts

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Abstract. In this paper, we consider the problem of medical images inpainting, where the goal is to reconstruct missing or damaged parts of the image. This is a good tool for medical applications such as vascular restoration, removal of specular reflections for endoscopic images, removal of MRI artifacts, etc. The new method combines the search for patches of various sizes and the operation of a pre-trained neural network. The large patches are used to reconstruct homogeneous areas, and then small patches are used to reconstruct structure image details. As a result, the proposed method provides a plausible of medical images inpainting. Experimental results demonstrate the effectiveness of the proposed method in the tasks of medical images inpainting.

1. Introduction

Image inpainting is a technique to remove the undesirable or filling missing (repair damaged) section from an image, by selecting patches from the rest of the image, or the class of images and placing these patches in the region/section using some “optimality” criterion. Most image inpainting methods can be divided into the following groups: methods based on the solution of partial differential equations (PDE); methods based on orthogonal transformations; methods based on texture synthesis; methods based on the operation of a neural network. Each of them has own advantages and disadvantages.

We consider in this paper the problem of image inpainting in medical image analysis, where the objective is to reconstruct missing or deteriorated parts of an image. It is a good tool for such medical applications as vascular reconstruction, specular reflection removal for endoscopic images, MRI artifacts removing, etc. Most inpainting approaches require a good image model to infer the unknown pixels. Such examples are:
- MRI and CT metal artifact reduction (Fig. 1).
2. Proposed method

2.1. Reconstruction method

At the first step, for each pixel of the boundary $\partial S_{i,j}$ using the inversion method the shape of the domain for similarity search is adaptively determined by combining two adjacent homogeneous subregions in the direction of the maximum gradient [2-6].

The second step calculates the priority value $P(\partial S)$ for each pixel value of the boundary, which consists of two factors [3, 5]:

$$P(\partial S) = C(\partial S) \cdot D(\partial S)$$  

$$C(\partial S) = \sum_{l \in \Psi_{\partial S}} \frac{C(l)}{|\Psi_{\partial S}|} \cdot D(\partial S) = \frac{\sqrt{I_{\partial S} \cdot n_{\partial S}}}{\alpha}$$  

Using the method proposed in the work [1] the entire image is preliminarily divided into patches of $5 \times 5, 7 \times 7, ... , 21 \times 21$, where large patches are used to reconstruct homogeneous areas, and then small patches are used to reconstruct structure image details (Fig. 4).
Next, in the third step, we determine blocks \( \psi_{q}^{(h)}, \ h = 1, R \) in the area of available pixels \( S \) for which the Euclidean metric is minimal \([4, 6, 8]\):

\[
\sqrt{\sum (\psi_{p} - \psi_{q})^{2}} \rightarrow \text{min}.
\] (3)

The pixel values in the region \( \eta \) adjacent to the pixel with the highest priority \( p \) are reconstructed by averaging the corresponding pixels from chosen areas \( \psi_{q}^{(h)} \) in the area of available pixels \( S \) using a neural network, in particular, a multi-layer perceptron[8].

The confidence coefficient \( C \) for restored pixels is assigned to the current value \( C(p) \).

After that, the procedure of priority correction and search of similar areas with subsequent replacement is repeated.

2.2. Neural network

In this work, a neural network of direct signal propagation, which was trained using the algorithm for back propagation of the error was developed. The activation function which is used in this network is the sigmoidal nonlinear function (sigmoidal nonlinearity), namely the hyperbolic tangent function \((4)[8-10]\).

\[
f(x) = \tanh\left(\frac{ax}{2}\right) = \frac{1-e^{-ax}}{1+e^{-ax}}
\] (4)

\( a \) - is the slope parameter of the sigmoidal activation function.

At the training stage of the neural network, pre-prepared data was fed to the input: a blocks with random coordinates \( 3 \times 3, 5 \times 5, 7 \times 7, \ldots, 21 \times 21 \) in size was allocated to the image, then the central pixel was removed, and five most similar blocks were found on the whole image comparing them by MSE.
Then the procedure was repeated on 35 images, and 100,000 blocks were obtained, they were used as a training sequence for this network. This network contains three layers [9]: the first layer contains 20 neurons, the second layer also contains 20 neurons, the third layer contains ten neurons (Fig. 5). The network created ten inputs, 5 of them were fed only the central pixels in the blocks found, and the other five inputs fed the MSE of these blocks. As an output, there were the central pixels of the original blocks.

3. Experimental results

To test the effectiveness of the proposed reconstruction method when deleting objects in the image, four test images were selected. The peculiarity of these test images is that the areas of missing pixels are located at the intersection of several borders. Figures 6-9 show examples of image restoration (a) of the original image, b) image with a mask of distorted pixels, c) image restored by the proposed method. The proposed method of image inpainting allows to “correctly” restore borders.

![Figure 6. Reconstruction example (a) the original image, b) image with a mask of distorted pixels, c) image restored by the proposed method.](image1)

It should be noted that the proposed method does not blur the texture and structure when restoring large areas with lost pixels. The proposed method allows you to correctly restore details on the image, and there is also the absence of artifacts when restoring lost blocks.

![Figure 7. Reconstruction example (a) the original image, b) image with a mask of distorted pixels, c) image restored by the proposed method.](image2)
Figure 8. Reconstruction example (a) the original image, b) image with a mask of distorted pixels, c) image restored by the proposed method.

Figure 9 shows an example of image recovery (a) the original image, b) image with a mask of distorted pixels, c) image restored by the proposed method. A feature of this image is that the area for restoration is at the intersection of several borders. The proposed method allows you to correctly restore the boundaries of objects.

Figure 9. Reconstruction example (a) the original image, b) image with a mask of distorted pixels, c) image restored by the proposed method.

The processing error values for the proposed method, EBM, Navier-Stokes and Telea methods [2] are presented in Table 1. It should be noted that the quantitative values of the errors are calculated in the reconstructed areas. When using the developed image reconstruction method, the error values are on average 10–15% less than when processed by EBM, Navier Stokes and Telea.

Table 1. Processing error values.

| Images | Fig. 6 | Fig. 7 |
|--------|--------|--------|
|        | $PP$   | $EBM$  | $NS$  | $Telea$ | $PP$   | $EBM$  | $NS$  | $Telea$ |
| $PSNR$ | 30.73  | 27.37  | 25.98 | 24.62   | 25.36  | 24.64  | 25.42 | 23.52   |
| $RMSE$ | 8.61   | 10.75  | 13.73 | 14.85   | 15.87  | 15.14  | 16.36 | 14.72   |
| $MAE$  | 3.55   | 4.72   | 5.34  | 7.81    | 7.11   | 7.8    | 7.68  | 7.93    |
| $SNR$  | 26.53  | 23.13  | 22.46 | 20.78   | 24.68  | 14.27  | 21.55 | 22.33   |

| Images | Fig. 8 | Fig. 9 |
|--------|--------|--------|
|        | $PP$   | $EBM$  | $NS$  | $Telea$ | $PP$   | $EBM$  | $NS$  | $Telea$ |
| $PSNR$ | 44.3   | 41.91  | 18.24 | 22.56   | 26.22  | 24.65  | 23.95 | 24.35   |
| $RMSE$ | 3.56   | 7.36   | 8.67  | 12.92   | 16.18  | 16.98  | 17.54 | 16.33   |
| $MAE$  | 1.5    | 2.35   | 3.87  | 4.68    | 6.18   | 6.95   | 6.25  | 5.95    |
| $SNR$  | 41.18  | 36.79  | 33.26 | 31.54   | 28.58  | 28.27  | 32.18 | 31.88   |
4. **Conclusions**
In this paper, a patch-based inpainting algorithm for MRI and CT metal artifact reduction has been developed. We used the method of splitting the image into patches of different sizes and a trained neural network to select the “best similar” patch. Analysis of the results indicates that the proposed method correctly restores both details and background of the medical image in case of the presents metal artifacts and produces 10-15% lower reconstruction errors, than widely used state-of-the-art methods.

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