Extension of Graph Cuts for a More Precise Segmentation used in Metal Artifact Reduction

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Introduction

Basic Situation

Metal artifacts tremendously impair the image quality of a CT scan. Most metal artifact reduction (MAR) methods base on the recomputation of the projection values that are influenced by metal objects using interpolation before the reconstruction. E.g. Meyer et al.[2] proposed a MAR approach that is a combination of an inpainting-based MAR method and a frequency split approach. The MAR result is a weighted sum of low and high frequency parts of the uncorrected and corrected projections, called frequency split MAR (FSMAR).

Challenges

Most MAR methods require a valid segmentation of the metal parts. The accuracy of the segmentation has a high influence on the quality of MAR[4]. The state-of-the-art approach uses a simple threshold to determine the metal object[4]. However, the segmentation of a metal object that induces streaks and shadows poses a non-trivial problem.

Our Approach

We present a novel approach of an automatic, object independent segmentation which starts with the state-of-the-art segmentation. This initial segmentation is improved by applying graph cut[1] onto every projection. We extend the graph cut idea by more information about the distance, a classification probability and a bias. By additionally considering global consistency, we receive a more precise segmentation result. For the evaluation, our new segmentation approach was combined with the FSMAR[2].

Metal Artifact Reduction

Metal Artifact Reduction

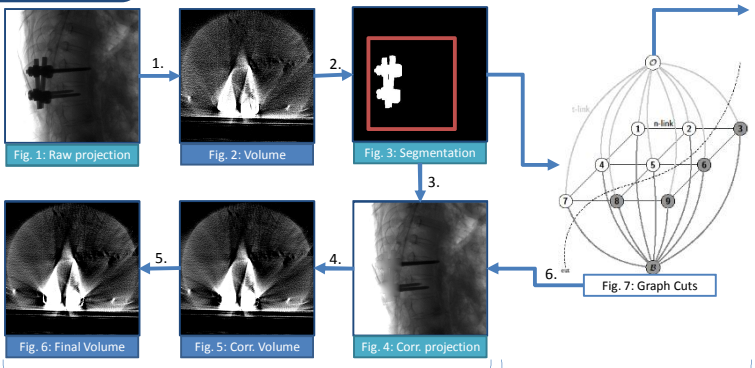
1. Reconstruct the raw projections (Fig. 1)
2. Segment the metal volume by applying a simple threshold to the volume (Fig. 2) and forward project the metal volume to receive the segmentation (Fig. 3) in projection space
3. Correct the artifacts in the projections by interpolating the metal regions (Fig. 4)
4. Reconstruct the corrected projections to receive a volume with reduced metal parts and reduced metal artifacts (Fig. 5)
5. Reintegrate the metal volume into the metal reduced and metal artifact reduced volume to get the final volume (Fig. 6)

Problem: Incorrect segmentation

6. Approach: Improve segmentation

New segmentation approach

I. Start with the raw projection (Fig. 8) and apply the state-of-the-art segmentation using a threshold of 0.7 times maximal intensity (= seeds, Fig. 9)
II. Use Otsu's Threshold[3] to determine background, foreground (O) and not known region (U), called trimap (Fig. 10)
III. Apply Graph Cuts, use trimap instead of user input and incorporate information:
   a. Bias
   b. Distance to known metal (Fig. 12)
   c. Classification probability (Fig. 11)
   d. Intensity distribution of O and B
   e. Weight a. to d. by trained parameters
IV. Receive segmentation result (Fig. 13)
V. Ensure global consistency by reconstructing (Fig. 14), thresholding (Fig. 15) and again forward projecting the result (Fig. 16)



Graph Cuts[1]

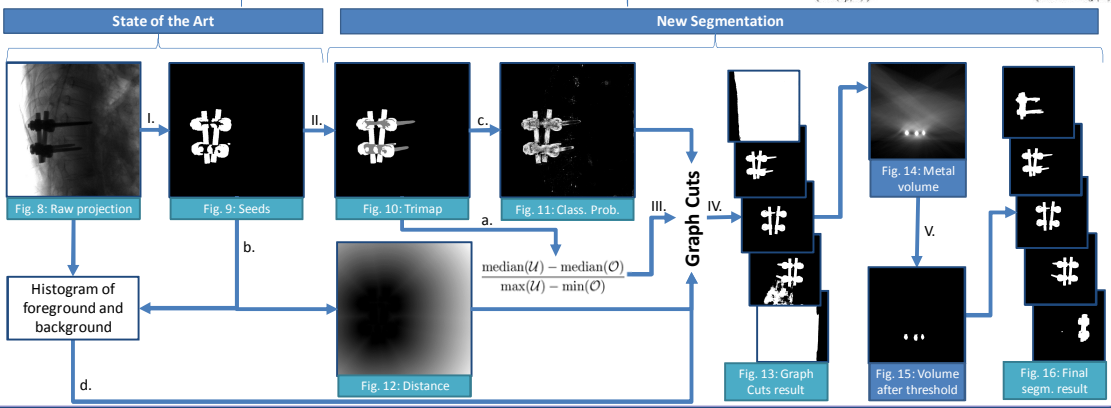
- Image is represented by a graph where the nodes correspond to pixels (Fig. 7)
- n-links connect neighboring pixels
- t-links connect pixels with special nodes O (object) and B (background)
- All links carry a weight according to the similarity of the connected nodes
- Optimal segmentation equals the division of the graph by a cut such that the summed up weights of the cut links is minimal
- Based on user input the initial probability of the pixels' intensities I_p belonging to O and B is calculated. Thus, the t-link for a pixel p equals

$$r(p) = \ln\left(\frac{P(I_p|\mathcal{O})}{P(I_p|\mathcal{B})}\right) \quad (1)$$

Our new approach bases on graph cuts but

- Uses trimap instead of user input
- Weights t-links with more precise r(p)

$$r(p) = \ln\left(\frac{Pr(I_p|\mathcal{O})}{Pr(I_p|\mathcal{B})}\right) + \alpha \cdot \text{bias} - \beta \cdot \text{dist}(p, m|\mathcal{O}) + \gamma \cdot \ln\left(\frac{\text{classProb}(p|\mathcal{O})}{\text{classProb}(p|\mathcal{B})}\right) \quad (2)$$



Results

We use more accurate the t-links by considering additional information. We weight these additional information according to trained parameters. We used a genetic algorithm with 50 individuals and 80 generations such that the number of wrong segmented pixels were minimized. We found the optimal parameter set:

- α = -84, β = 10, γ = 1
- λ = 70 (relative importance of n-links and t-links)

We used the training data sets thorax, heel, knee, elbow.

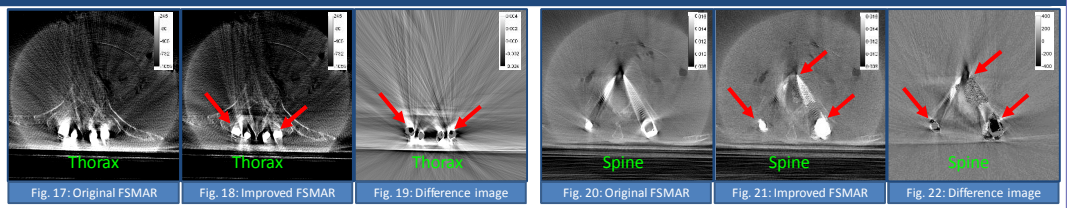


Fig. 17: Original FSMAR | Fig. 18: Improved FSMAR | Fig. 19: Difference image | Fig. 20: Original FSMAR | Fig. 21: Improved FSMAR | Fig. 22: Difference image

Using our new approach, we improved the segmentation significantly. Thus, also the FSMAR[2] yields better results basing on our improved segmentation (see Fig. 18 and 21) than the FSMAR using the state-of-the-art segmentation applied to the thorax and spine data set shown in Fig. 17 and 20, respectively. We could reduce the metal artifacts, i.e. less streaks and shadows and achieved a higher diagnostic value. We highlighted the major regions of improvement by red arrows in both data sets. In order to show the improvement clearly, the difference images for the thorax and spine data set are given in Fig. 19 and 22.

Discussion & Outlook

We could improve the segmentation of metal objects in mobile C-arm CT images and received a MAR result of higher quality compared to FSMAR using the state-of-the-art segmentation. In future work, the segmentation using graph cuts in higher dimensions should be considered in order to receive an even more reliable segmentation. Furthermore, applying our proposed approach to projections without metal objects should be discussed.

Acknowledgements & References

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Six mobile C-arm CT data sets (data courtesy of Prof. Dr. U. Stöckle, Prof. Dr. B. König, Dr. A. Schäffler from Klinikum rechts der Isar, Center of Trauma Surgery and Siemens Healthcare DI XP TEC IG) have been used.

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