Reduction of Intravenous Contrast Related Artifacts in CT-Based Attenuation Corrected PET Images

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Abstract — **A well established advantage of using contrast-enhanced CT in dual-modality PET/CT imaging is the possibility to obtain diagnostic quality CT images, thus allowing to increase patient throughput and reduce patient absorbed dose. However, the use of CT data following intravenous (IV) injection of contrast media for attenuation correction might bias the attenuation-map (µmap) and generate visible artifacts on reconstructed PET images owing to the misclassification of contrast-medium with high density bone when using standard procedures for conversion of CT numbers to linear attenuation coefficients at 511 keV. In this study, an algorithm for segmentation and classification of irregular shapes of regions containing IV contrast-medium usually found in clinical CT images is proposed and assessed using clinical data. The proposed automated three-dimensional segmentation method consists of two steps: firstly all objects with high CT number are segmented based on a region-based segmentation method in conjunction with boundary-based segmentation to reduce mis-segmentation of objects. Second, the process of object classification to separate bones and contrast-medium is carried out using a fuzzy classifier as knowledge based nonlinear classifier. Thereafter, either the CT numbers of pixels belonging to the regions segmented as contrast medium are substituted with their equivalent effective bone CT numbers based on segmented contrast correction (SCC) algorithm, or the classified regions as contrast medium can be converted to µmap using different calibration curves for energy mapping. The generated CT images were down-sampled followed by Gaussian smoothing to match the resolution of PET images. The bi-linear calibration curve was used to convert CT pixel values in HU to µmap at 511 keV. The visual assessment of segmented regions in clinical CT images by an experienced radiologist confirmed the accuracy of the algorithm for delineation of contrast enhanced regions. The results illustrate the difference between attenuation coefficients in the generated attenuation maps before and after SCC. Quantitative analysis of the generated µmaps from a clinical study showed an overestimation of 23.4% of attenuation coefficients in the 3D regions classified as contrast-medium. The algorithm is being refined and further validated in clinical setting to enable the application of this algorithm in PET/CT clinical arena.**

Keywords — **Intravenous, Contrast medium, Attenuation Correction, CT, PET**

I. Introduction

Today, X-ray CT images are utilized to generate valuable and noiseless attenuation correction factors for the PET emission data in addition to using for accurate anatomic localization of functional abnormalities seen on PET scans. However iodinated contrast is used in order to enhance the diagnostic quality of CT image, but it makes incorrectly scaled to 511 keV and potentially generates focal artifacts in the PET image. It must be emphasized although using contrast medium leads to more effective diagnosing imaging in the CT images but this would be an undesirable outcome in PET, particularly for tumor imaging [1].

One of the well implemented methods for the correction of oral and intravenous contrast medium artefact in CTAC PET images, called segmented contrast correction (SCC) method, was originally proposed by Nehmeh et al [2]. The main problem in clinical use of SCC algorithm is the difficulty in segmentation and classification of bone and contrast medium in patient's CT image. Generally, Bone and contrast medium segmentation is not an easy task and need special consideration. Bones come in a variety of shapes and have a complex internal and external structure with similar or higher CT values than other tissues which overlap by density range of contrast medium [3].

In preliminary studies related to contrast agent segmentation, a manual segmentation was performed, which is a difficult task in large volume database [2]. In another work, Carney et al. used region growing for high CT number (HCTN) object segmentation and assumed the largest objects as a bone [4]. Yao identifies and removes bone from the contrast-enhanced CT image via three methods: Template matching, region growing, and snake based, then the contrast-enhanced tissue from the rest of the image is separated by a threshold [5]. All of them are blind bone segmentation and do not use any feature for classification of bones from contrast medium. In our previous work, the new approach has been proposed in order to segment and classify oral contrast medium from bones [3].

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In this study, an algorithm for segmentation and classification of irregular shapes of regions containing IV contrast medium was proposed for wider applicability of the SCC algorithm in order to correct the IV contrast artefacts in CTAC. This algorithm is the extended version of our algorithm for segmentation of oral contrast [3] and covers the limitation of previous algorithm in segmentation and classification of small regions containing contrast medium with low CT number (150 – 350 HU).

II. MATEIALS AND METHOD

A. HCTN Segmentation

In SCC algorithm the contrast medium that enters the vein or penetrates in tissues such as liver or kidney must be segmented for further correction. It is well known that simple methods such as thresholding and region growing are usually not sufficient for complicated tasks. These methods do not employ border properties that can lead to wrong segmentation but boundary-based methods can help to overcome this problem. Meanwhile integrating the results of the boundary-based approach with region-based method overcome the weak segmentation. We used our previous proposed method for HCTN objects segmentation [3]. This method utilizes combined region- and boundary-based segmentation techniques. This hybrid method is proposed due to the complexity of this task; Contrast medium identification is not a simple task due to the unknown shape of regions containing contrast medium and completely various CT Numbers of these regions that can vary between 100 HU to 4096 HU depending on their concentration. This range overlaps with marrow density that is slightly above that of soft tissue and with high density parts of bone. In addition, bone segmentation has its own problems: Irregular shapes of bones with different complex internal and external structure in addition to slight borders that are observed widely in trabecular bones due to partial volume averaging effect. Therefore, the hybrid method has been proposed to overcome this complexity. By this method, the canny edge operator was performed as an edge detector. The combination of obtained edges and HCTN objects that was used as a selected region and special seed lead to more complete HCTN objects segmentation. This stage leads to HCTN objects segmentation that consists of bones that are included inner parts – marrow- and high density contrast medium. In the next step, extracted features will be used for discrimination. Figure 1 shows different steps of algorithm.

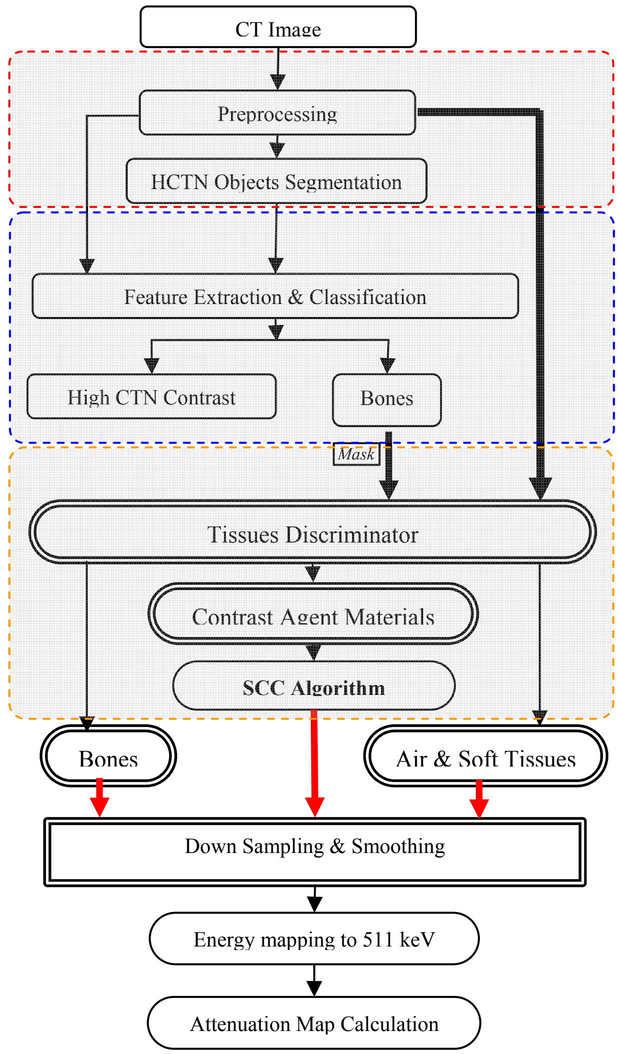

Fig. 1. Flowchart illustrating the different steps of the algorithm used for segmentation and correction of IV contrast artifacts in CTAC.

B. Feature Extraction and Classification

During this stage, the features used for classification include volume, mean, minimum, maximum, variance, and recursive mean of outer layer's object. The recursive layer mean is one of the most important features that rely on the fact that the bone's marrow density is less than outer bone area; however, Intravenous contrast medium has a uniform density distribution in the majority of cases in regions with high concentration of contrast medium. This feature is computed using object's outer surface CT values after erosion using a recursive algorithm. Classifiers utilize features to classify the objects with different pattern and feature space. Among available classifiers, fuzzy logic improves the classification and decision support systems by allowing the use of overlapping class definitions in addition to improving the interpretability of the results. In this study, we applied the Mamdani-type fuzzy classifier, which uses rules describing each class of customers [6].

C. Contrast medium Recognition

The previous stages lead to bone identifications that are high density parts of images. Meanwhile there are two categories for contrast materials: first, the HCTN parts that are segmented and recognized in the last stage and the contrast material with lower CT Number that are not recognized yet due to the slightly high threshold of previous stage (350 HU). We have to use this threshold in segmentation stage; Lower threshold lead to a lot of wrong objects that are bothersome. However this high threshold causes missing of some tissues that contained small amount of contrast medium, mostly have CT number between 150 – 350 HU. To overcome this problem, firstly the bone mask has been used for separation of HCTN objects that are surely belonging to bone parts. Consequently, the remained tissues are classified to soft tissue and region that contained contrast medium using a binary classifier. 150 HU is a confident threshold because of lower probability density function of soft tissue in x-ray CT images. It must be considered that the region with this low CT Numbers 100 – 200 HU have meaningless difference by the SCC algorithm and normal method and does not lead to reconstruction artifact [7].

D. Attenuation correction and image reconstruction

The CT-based attenuation maps at 511 keV derived from the clinical CT data sets were generated as follows. The CT images were first down-sampled to 128×128 followed by Gaussian smoothing to match the spatial resolution of the PET scanner. The CT numbers were then transformed to linear attenuation coefficients at 511 keV using the calculated bi-linear calibration curve based on the method proposed by Bai et al. [8]. The bilinear calibration curve in order to use for energy mapping was calculated by scanning of a dedicated in-house phantom [9] in the LightSpeed VCT 64 slice CT scanner (General Electric Healthcare Technologies, Waukesha, WI) at 120 kVp and 200 mAs. The images were then corrected for the presence of contrast medium using the segmentation algorithm described in previous sections.

III. Result

The assessment of CTAC accuracy in the presence of Intra Venous contrast agent was performed using 5 clinical X-ray CT datasets. Figure 2 illustrates the segmentation process and implementation of the SCC algorithm to a clinical CT study. In Fig. 2b, the regions containing IV contrast medium are labelled with green and the bone regions are labelled with red colour. The visual assessment of segmented regions from clinical CT images performed by an experienced radiologist confirmed the accuracy of the algorithm for delineation of contrast enhanced regions. Fig 2(c-d) shows the segmented bone objects and contrast agent objects, respectively. Fig. 2e shows the original CT image after substitution of CT numbers in the contrast enhanced regions with their equivalent effective bone CT numbers using the SCC algorithm. Fig. 2(f-g) shows the μmap generated from original CT (Fig 2a) and CT images after applying the SCC algorithm (Fig. 2e). Figure 2h shows the difference between uncorrected and corrected μmap. Figure 2i shows a profile through μmaps to illustrate the difference between attenuation coefficients in the generated μmaps before and after SCC. Quantitative analysis of the generated μmaps from a clinical study showed an overestimation of 23.7% of attenuation coefficients in the 3D regions classified as contrast agent. The visual assessment of segmented regions from clinical CT images performed by an experienced radiologist confirmed the accuracy of the algorithm for delineation of contrast enhanced regions.

IV. Discussion and conclusions

We developed an automated segmentation algorithm for the classification of irregular shapes of regions containing contrast medium usually found in clinical CT images for wider applicability of the SCC algorithm for the correction of contrast medium artefacts in CTAC. Although combined PET/CT scanners has several substantial benefits such as noise free attenuation map and increasing accuracy in lesion localization but it has the potential for significant bias in the ACFs in regions containing high concentrations of contrast medium. The SCC algorithm, proposed by Nehmeh et al is one the most efficient algorithm for the correction of contrast agent artefact. Meanwhile one of the main challenges in the implementation of SCC algorithm is accurate segmentation and classification regions containing contrast media. In this study, we developed an automated algorithm for segmentation and classification of regions containing contrast medium in order to correct for artifacts in CT attenuation-corrected PET images using the segmented contrast correction (SCC) algorithm.

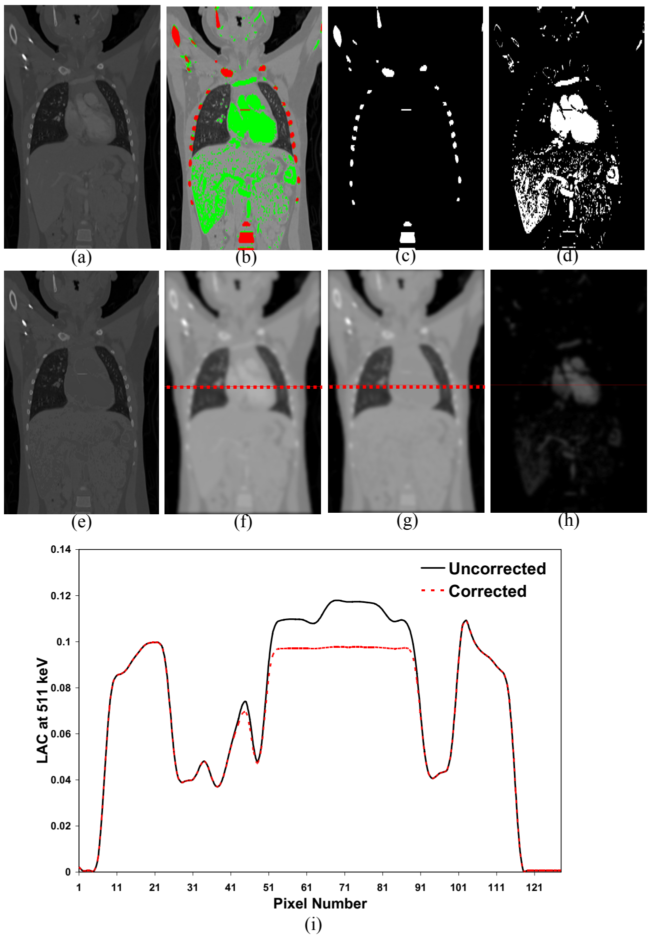

Fig. 2. Original IV contrast enhanced CT image (a), segmented CT image (b), bone objects (c), contrast agent objects (d), original contrast enhanced CT image after applying SCC to the regions segmented as containing contrast agent (e), generated μmap from original CT (f), and generated μmap after SCC (g), difference between uncorrected and corrected μmap (h), Horizontal profiles (position shown in f-g) through generated attenuation maps before and after applying SCC (i).

The basic idea of this work was based on automatically recognition of contrast mediums that are spread out in the body. Unfortunately, contrast mediums like bones have completely various densities range, irregular shape spreading in different area that makes it a challenges task. To overcome this problem, we proposed a sophisticated classifier based on extracted features in addition to hybrid method for complete segmentation of the desired region. The Visual assessment by an expert radiologist confirmed the result of contrast medium segmentation and classification that is acceptable with hybrid method and is obvious that it could reduce the unfavorable effect of CEF in reconstruction process. It must be considered that the new proposed method resolve the contrast medium problem with density range of 150 – 350 HU. The algorithm is being refined and further validated in clinical setting to enable the application of this algorithm in PET/CT clinical arena

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