RESEARCH ARTICLE

Statistical iterative reconstruction for streak artefact reduction when using multidetector CT to image the dento-alveolar structures

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Objectives: When metallic prosthetic appliances and dental fillings exist in the oral cavity, the appearance of metal-induced streak artefacts is not avoidable in CT images. The aim of this study was to develop a method for artefact reduction using the statistical reconstruction on multidetector row CT images.

Methods: Adjacent CT images often depict similar anatomical structures. Therefore, reconstructed images with weak artefacts were attempted using projection data of an artefact-free image in a neighbouring thin slice. Images with moderate and strong artefacts were continuously processed in sequence by successive iterative restoration where the projection data was generated from the adjacent reconstructed slice. First, the basic maximum likelihood–expectation maximization algorithm was applied. Next, the ordered subset–expectation maximization algorithm was examined. Alternatively, a small region of interest setting was designated. Finally, the general purpose graphic processing unit machine was applied in both situations.

Results: The algorithms reduced the metal-induced streak artefacts on multidetector row CT images when the sequential processing method was applied. The ordered subset–expectation maximization and small region of interest reduced the processing duration without apparent detriments. A general-purpose graphic processing unit realized the high performance.

Conclusions: A statistical reconstruction method was applied for the streak artefact reduction. The alternative algorithms applied were effective. Both software and hardware tools, such as ordered subset–expectation maximization, small region of interest and general-purpose graphic processing unit achieved fast artefact correction.

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Introduction

Statistical reconstruction has been developed for noise reduction on images and radiation exposure reduction to patients.^{1–8}

When CT examinations are carried out to image the dental–alveolar region and there are metallic prosthetic appliances and restoration dental materials in the oral cavity, the appearance of metal-induced streak artefacts is not avoidable.^{9–14} Fixed metallic prosthetic appliances are usually made from high atomic number, high-density materials. Similar artefacts are also observed by the presence of other metallic biomaterials.^{15–21} The streak artefacts caused by metallic materials on multidetector row CT (MDCT) images are intense and radial.

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Figure 1 An example of computing the projection data of a 256 × 256 pixel matrix image. Each row in the projection data represents the detectability value of the detector for a designated angle. The projection data were acquired in 360 directions with 1° intervals, so the pixel matrix was 256 × 360.

Metallic biomaterials that are not only in the oral and maxillofacial region but also in other body regions cause loss of portions of the projection data owing to extremely high X-ray absorption coefficients.^{12,13,19,21} Resulting sinogram patterns show the image corruption from such missing data. The traditional CT reconstruction method, the filtered back-projection algorithm, cannot deal with such metal-induced inconsistencies. Hence, several alternative algorithms have been proposed for metal-induced streak artefact reduction.^{12,13,15–19,21} These repair the partly corrupted sinogram data by either the replacement by intact data or by interpolation.

Statistical reconstruction algorithms are an old idea for image construction; however, they can be considered relatively new technology when applied to quality improvement of CT images.^{1,2,4–6,8,9,21–24} In previous studies, statistical reconstruction algorithms have been applied not only for image-quality improvement but also for streak artefact reduction.^{22–24} The present investigation focused on the fact that there were artefact-free slices next to slices with heavy streak artefacts and that such slices depicted morphologically almost identical portions of anatomical

structures. The maximum likelihood–expectation maximization (ML-EM) reconstruction algorithm was attempted with successive iterative restoration to reduce metal-induced streak artefacts.^{22,23}

Previously, Kondo et al²² used the ML-EM algorithm to process an MDCT slice with heavy artefacts by using the projection data of the artefact-free slice on the neighbouring slice. There were seven slices (0.5 mm for a single slice) between the slice being processed and the artefact-free slice. Dong et al²³ applied the successive iterative restoration method.

Statistical reconstruction algorithms usually necessitate a huge amount of computational effort and are sometimes termed the algebraic reconstruction technique. The ML-EM algorithm, which was used in previous studies, was a very time-consuming procedure.^{22,23} It took more than 6 min to reconstruct a 512 × 512 pixel matrix image for 50 cycle iterations using a desktop personal computer.²³ Subsequently, Dong et al²³ applied the ordered subset–expectation maximization (OS-EM) algorithm as a solution to speeding up computation.²⁴ Further performance improvement was achieved by using a small region of interest (ROI) setting combined with successive and reverse processing methods.²⁴

The purpose of the presently reported study was to investigate the use of a very small ROI setting and fast calculation by the compute unified device architecture (CUDA) programming optimized for the general-purpose graphic processing unit (GPGPU).

Methods and materials

Image acquisition

In this report, MDCT image volumes used for the clinical diagnosis of the jaw deformity were processed.

Table 1 Execution steps of maximum likelihood–expectation maximization algorithm

Execution steps	Procedures
Step 1	Select the top (“headmost”) image. Usually, this is an image containing streak artefact. Set this as the initial image
Step 2	Calculate the detecting probability
Step 3	Compute projection data of initial image. Then, compare it with the projection data of the intact image in matrix pixel sequence
Step 4	Reconstruct the assumed image according to the projection data ratio obtained in Step 3
Step 5	Normalize the reconstructed image and set as the new initial (“headmost”) image
Step 6	Repeat Steps 3–5 until achieving the iteration time setting

Figure 2 Continuous six original (unprocessed) maxilla slices. They are aligned from head to foot, from no. 1, in the far left in the top row, to no. 6, in the far right in the bottom row. The slices were obtained before the jaw deformity treatment operation. No orthodontic device or titanium plate was present.

The subject was a 32-year-old female at the time of pre-surgical imaging and had been subsequently re-imaged following surgery. An institutional review board approval was forthcoming. The subject consented to the use of her CT images for this study. The image volumes were acquired using a LightSpeed® VCT (GE Healthcare, Waukesha, MI). The exposure parameters were 120 kV and 361 mAs, and the slice thickness was 1.3 mm. The pixel matrix of each slice was 512×512 . Severe metal-induced streak artefacts occurred owing to several metallic tooth crowns in the maxilla and mandible and orthodontic appliances.

Projection data acquisition

Projection data acquisition was carried out as described in previous reports.^{22–24} Each pixel of the image has a CT number, which is proportional to radiographic transparency. When the X-rays traverse each pixel the shape of each pixel is usually a trapezoid, depending on

the angle between the projection and each pixel square. In special cases, projection shapes of square pixels become either a square at 0° , 90° , 180° and 270° or a triangle at 45° , 135° , 225° and 315° when the coordinate axes are set along edges of the image (Figure 1). The image matrix contained 512 pixels. During the detectability calculation, the value is accumulated by adding the CT number of the respective pixels. If the shape of the projection is not a square, the detectability will be divided by the centre of the detector element and neighbouring elements. The projection data were acquired in 360 directions with 1° intervals, so the pixel number was 512×360 .

Successive iterative restoration

Generally, CT examinations with thin slice thicknesses are carried out in the dento-alveolar region, and adjacent CT slices often depict very similar anatomical structures. The current trial was to reconstruct the CT image containing streak artefacts using the projection data of the adjacent image.^{22–24}

In previous studies, we compared two different processing methods.^{23,24} First, we obtained the projection data of the artefact-free image. Continuous neighbouring images were processed using the same intact image's projection data.²³ Alternatively, while the projection data acquisition of the artefact-free image was carried out similarly, projection data to reduce the artefact used only the immediately adjacent slice. After the slice was reconstructed, the projection data of the processed image were obtained, and then applied to process the neighbouring slice; and so on, using the “successive” iterative restoration method for processing

Figure 3 An artefact-free image with the projection data to its right. The artefact-free image is the adjacent image to the far left one in the top row of Figure 2.

Figure 4 Resultant images processed by successive iterative ordered subset–expectation maximization algorithm presented in the same sequence as in Figure 2.

all images.²⁴ For the present report, the successive method was employed.

Iterative restoration: maximum likelihood–expectation maximization and ordered subset–expectation maximization methods

For the iterative restoration method, we used two algorithms, namely, ML-EM and OS-EM. The ML-EM algorithm results in an approximation between the

processing image and the target image. The formulation of ML-EM algorithm is described as follows:

$$\lambda_j^{(k+1)} = \frac{\lambda_j^{(k)}}{\sum_{i=1}^n C_{ij}} \sum_{i=1}^n \frac{y_i C_{ij}}{\sum_{j'=1}^m C_{ij'} \lambda_{j'}^{(k)}}$$

where, λ (lambda) is the output value of each pixel; k , the counter of iteration (loop variable); j , the number of

Figure 5 Continuous seven original (unprocessed) maxilla slices from head to foot. The image volume was obtained after surgery. The orthodontic wire and brackets, bone screws or titanium plates can be observed on some specific CT slices.

Figure 6 An artefact-free image and its projection data. The artefact-free image is the adjacent image to the far left one in the top row of Figure 5.

pixels $(1 - m)$, $m = 262,144$ if the image matrix is 512×512 ; i , the number of detector elements $(1 - n)$; C_{ij} , detecting probability as the relation of pixel (i) and detector element (j) ; and y_j , the projection data by the pixel (i) .

We applied the ML-EM algorithm to reconstruct images following the steps shown in Table 1. An artefact-free image is needed to process a CT image having streak artefacts (Step 1). Based on the projection data acquisition rules, the projection data of two images can be calculated (Step 2). Then, the two projection data sets are compared pixel by pixel. When the values are different, the pixel value, which belongs to projection data of artefact-containing image, is modified to another value. The new value must be calculated using the value of projection data of the artefact-free image as a reference (Step 3). After every pixel is compared on the projection data, new projection data are produced. Next, the back-projection operation is executed based on the newly produced projection data (Step 4). Then, a new image, which contains both features of the

artefact-free (or artefact-reduced) and artefact-containing images, can be obtained (Step 5). More iterative operations will lead to the new image displaying features of the artefact-free image dominantly (Step 6). Of these steps, the key procedure is the process of comparing the projection data of the intact and the newest one and, then, making an approximation between them.

The OS-EM algorithm was also used as the successive iterative reconstruction algorithm in this work the same as a previous work.²⁴ The OS-EM algorithm, which is based on the ML-EM algorithm, divides the projection data into several subsets and carries out the projection, comparison, back projection and renewal to only the data belonging to the given subset. Suppose that there are 24 projection angles in calculating the projection data, the 24 projection angles can be divided into 1, 2, 3, 4 or 6 subsets. For the OS-EM algorithm, the image-quality factor, namely the image update number, is the product of subset numbers and iteration times (image update number = subset number $\times$ iteration times). Therefore, there will be more image updates during a one-time iteration and, as a result, images can be reconstructed quickly. In our previous report,²⁴ combinations of subset numbers (either 4 or 8) and iteration numbers (either 5 or 10) were examined, and as a result, the optimal combination of a subset number and iteration times was derived to be subset = 8 and iteration = 10, and streak artefacts could be utmost reduced on this condition. Then, we chose this combination decisively in this study.

The processing was executed based on the C-language program. The performance of the computer that we

Figure 7 Reconstructed images by successive iterative ordered subset-expectation maximization algorithm. They correspond to the seven images in Figure 5.

Figure 8 Volume-rendered images of maxilla. The left image is reconstructed by merging ten sequential multidetector row CT (MDCT) slices from Figure 5. These are before streak artefact reduction. The middle one is reconstructed by merging ten MDCT slices from Figure 7. These are following streak artefact reduction. Superimposing of volume-rendered images are used to compare the three-dimensional renderings before and after surgery (right image).

used was as follows: an Intel® Core™ 2 Duo central processing unit (Intel Corporation, Santa Clara, CA), running at 3.16 and 2.83 GHz and a Windows® Vista operating system (Microsoft Corporation, Redmond, WA).

Region of interest setting

Because streak artefacts appeared only surrounding the teeth, we did the segmentation to CT slices only for the region of the teeth. A simple rectangular ROI was used for the segmentation each time. The projection data were calculated from only the tooth area; therefore, the density of the central part became brighter in the projection data image (sinogram), and the soft-tissue components seemingly disappeared at the image periphery.

Compute unified device architecture programming for general-purpose graphic processing unit machine

A high-performance GPGPU machine was used to execute the streak artefact reduction algorithm. Three CUDA-supporting graphic processing units, NVIDIA GeForce® GTX 680, were installed. The programming language used was CUDA, which is a specific C-language programming necessary for the powerful operation of GPGPU machines. A kernel function in the device code can divide a process into synchronous multithreads. According to the steps of successive iterative OS-EM algorithms, the procedure for calculating the projection data was repetitively executed iteration times. The projection data calculating procedure was

divided into synchronous multithreads according to projection acquisition angles.

Results

Images shown from Figures 2 to 7 are from a jaw deformity (mandibular retraction) case. Images shown in Figure 2 are original images. They were acquired as the pre-operative evaluation of bone morphology in the mandible for jaw deformity treatment. No orthodontic devices or titanium plates were present. Figure 3 is an artefact-free image, which is the adjacent image to the far left one in the top row in Figure 2. Its projection data (sinogram) is illustrated on the right. As indicated in the methodology, the OS-EM successive iterative restoration algorithm was applied on images. The resultant images are shown in Figure 4, and they correspond to the order of images shown in Figure 2. On the original images in Figure 2, streak artefacts occurred from several tooth crown metallic restorations. Processing substantially reduced the streak artefacts (Figure 4).

After receiving 3 years of orthodontic treatment, the patient had a surgical operation, using a sagittal split ramus osteotomy. The CT images shown in Figure 5 were scanned for the post-operative diagnosis. The orthodontic wire and brackets, bone screws or titanium plates can be observed on some specific CT slices. The

Figure 9 Region of interest (ROI) images of sequential images no. 1 to no. 4 in Figure 5. A part of the left mandible was segmented as a small ROI. These are original images without processing. The pixel matrix for the ROI images is 166×196 .

Figure 10 An artefact-free small region of interest setting image. This was segmented from the artefact-free image of Figure 6.

image in Figure 6 is an artefact-free image, which is attached with the projection data (sinogram), and it is the adjacent image to the far left one in the top row of Figure 5. As explained in the methodology, the OS-EM successive iterative restoration algorithm was applied. The resultant images are shown in Figure 7, and they correspond to the order of images shown in Figure 5. The original images in Figure 5 show streak artefacts that were intense. The artefacts were caused not only by dental restorative materials but also by the orthodontic wire, brackets and titanium plates. On the resultant images in Figure 7, streak artefacts caused by every kind of metallic material were reduced effectively. Tooth shape reverted to the original states on the former images, while some false anatomical structures occurred in the incisor and cuspid areas on the latter images.

In addition, we reconstructed three-dimensional (3D) images using images from Figures 5 and 7. The OsiriX (v.4.1.2, OsiriX Foundation, Geneva, Switzerland) 3D medical and photographic digital imaging and communications in medicine viewer was used. The resulting 3D images are shown in Figure 8, and they represented only a thin part of the maxilla. The left and middle images in Figure 8 were merged, respectively, from slices where the streak artefacts appeared (Figure 5) and were reduced (Figure 7). The image on the right of Figure 8 presented a simultaneous visualization of the left and middle images with different colours. The difference of streak artefact appearances can be obviously recognized by viewing 3D images in Figure 8.

Irregular artefacts, which were caused by the orthodontic wire and brackets, were observed at specific CT slices. Then, we applied a very small ROI setting segmented from original images no. 1 to no. 4 of Figures 5 and 9. The image in Figure 10 is an artefact-free image, which is attached with the projection data (sinogram). It is the adjacent image to the far left one in Figure 9. As explained in the methodology section, the OS-EM successive iterative restoration algorithm was applied on segmented images. Resultant images are shown in Figure 11, and they correspond to the order of Figure 9. Because of the decreasing calculation loading, the processing duration time reduced to 10.4 s for reconstructing a single small ROI setting image, while it was 84 s for a single original-sized CT slice. In the original ROI images, streak artefacts seriously damaged the image quality, and on the resultant images in Figure 11, the tooth shape reverted to its original state clearly and streak artefacts were also reduced effectively for both teeth and soft tissues.

As result of the calculation acceleration, the execution time was substantially reduced than when not using GPGPU. The computational loading comparison is given in Table 2.

Discussion

In previous studies, successive iterative ML-EM and OS-EM algorithms were proven to be effective in reducing streak artefacts on dental and maxillofacial MDCT images.^{22–24} It was decided to select the successive iterative OS-EM algorithm in this study, as it is more time saving than the ML-EM algorithm. Another key point is that the image can be reconstructed to approximate to the targeted image using less iteration times.²⁴ The successive iterative correction can present a good result in streak artefact reduction and anatomical structure recovery because adjacent CT slices often depict very similar anatomical structures nearby thin-thickness slices.

Very small ROI segmentation was employed in this study. There are two advantages of the small ROI image segmentation. On one hand, during image reconstruction, influences from other tissue structures were removed. On the other hand, the processing time

Figure 11 The reconstructed region of interest images by successive iterative ordered subset–expectation maximization algorithm, the order corresponds to the sequence of images in Figure 9.

Table 2 The computational loading comparison concerned with different algorithms and the general-purpose graphic processing unit (GPGPU) runtime environment

Successive iterative restoration	Execution parameters	Processing time
Maximum likelihood–expectation maximization	50 times iteration	6 min 10 s
OS-EM	8 subsets/10 times iteration	1 min 24 s
OS-EM on GPGPU	8 subsets/10 times iteration	20 s

OS-EM, ordered subset–expectation maximization.

for reconstructing each image was significantly shortened. By using the small ROI segmentation, the streak artefact reduction and anatomical structure recovery were realized satisfactorily.

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