A NOVEL INTENSITY LIMITING APPROACH TO METAL ARTEFACT REDUCTION IN 3D CT BAGGAGE IMAGERY

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ABSTRACT

This paper introduces a novel technique for Metal Artefact Reduction (MAR) in the previously unconsidered context 3D CT baggage imagery. The output of a conventional sinogram completion-based MAR approach is refined by imposing an upper limit on the intensity of the corrected images and by performing post-filtering using the non-local means filter. Furthermore, performance is evaluated using a novel quantitative analysis technique, using the ratio of noisy 3D SIFT detection points identified, as well as a standard qualitative comparison (visual quality). The objective of the quantitative analysis is to evaluate the impact of MAR on the application of computer vision techniques for automatic object recognition. The study yields encouraging results in both the qualitative and quantitative analyses. The proposed method yields a significant improvement in performance when compared to algorithms based on linear interpolation and reprojection-reconstruction; especially in terms of reducing the occurrence of new artefacts in the corrected images. The results serve as a strong indication that MAR will aid human and computerised analyses of 3D CT baggage imagery for transport security screening.

***Index Terms*—** Metal Artefact Reduction, baggage CT, 3D SIFT

1. INTRODUCTION

Baggage screening as a means of weapons and explosive detection, in the airport security setting, has become a ubiquitous practice worldwide. Traditionally, X-ray based 2D imaging technologies have been used for this purpose [1]. Recently, however, the use of 3D CT-based screening systems have become more widespread [2]. For both technologies (X-ray and CT), screening for weapons and complex contraband objects is performed by human operators, while automated detection is generally limited to materials-based explosives discrimination [3]. Recent studies have investigated the implementation of computer vision techniques, such as automatic object recognition, in the domain of 3D baggage screening [4, 5]. Such techniques however, are severely limited by the presence of noise and artefacts in CT images [4].

Metallic objects are a major cause of streaking artefacts in CT imagery. Due to their higher density and particularly their higher atomic number, metals attenuate X-rays in the diagnostic energy range much more strongly than other common materials. A metal substance can in fact attenuate the X-ray beam so strongly that virtually no photons reach the detectors (photon starvation effect), resulting in projections with corrupted and/or completely missing data. The resulting noisy regions in these corrupted projections are greatly magnified by the logarithmic operation in the Filtered Back Projection (FBP) algorithm used in the standard CT image reconstruction process [6], leading to artefacts in the reconstructed images. These artefacts generally manifest as unusually bright borders surrounding the metal objects and severe star-shaped streaks emanating from the surface of the metal object. Furthermore, any additional artefacts (due to beam hardening, partial volume, and aliasing etc...) are likely to be greatly exaggerated when scanning metal objects [7] (see Figure 1).

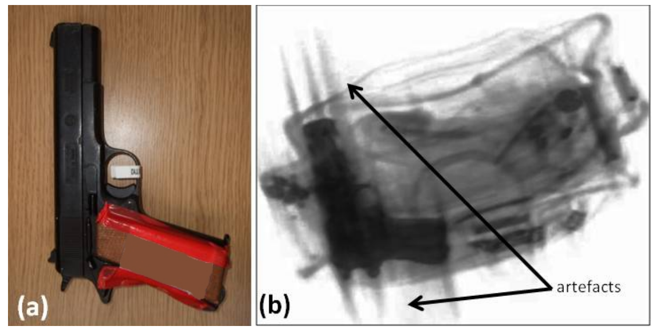

Fig. 1. Original object (a) with corresponding 3D CT scan (b) with metal artefacts indicated.

Considerable MAR-based research has been conducted in the medical field. In general, these techniques fall into one of three categories: sinogram (or projection) completion-based methods [8, 9]; iterative reconstruction methods [10, 11] or hybrid methods (combining completion and iterative methods) [12]. While it is widely accepted that iterative reconstruction techniques have several advantages over the standard FBP reconstruction process (especially in terms of reconstruction from incomplete and/or corrupted projection data), they involve processing massive quantities of raw projection data and the associated high computational cost has prevented their universal implementation [11]. Consequently, the vast majority of existing MAR techniques fall into the sinogram completion category, whereby missing/corrupted data in sinogram space is replaced via interpolation [8, 9]. Despite their popularity, however, the reliability of many pure interpolation-based approaches decrease considerably when considering large and/or multiple metal objects [9, 13].

Several recent studies have attempted to combat this using a number of approaches including: pre-filtering [14]; multiclass segmentation [8]; sinogram normalisation [9] and wavelet multiresolution interpolation [13]. These methods, however, often involve fine tuning several parameters and rely heavily on the inevitability of the structures present in the scan. Since they are all intended for use in the medical field, it is appropriate to assume that the scanned region will contain common anatomical structures, making the setting of dependent parameters more straightforward. In the baggage setting, however, this predictability is not available, making the selection of parameters significantly more challenging (e.g. see clutter in Figure 1).

The highly complex nature of baggage CT scans, coupled with the presence of multiple, large metallic objects (e.g. several firearms in a single scan) indicates that the shortcomings of pure interpolation-based approaches will be particularly prominent with such data. We thus propose a novel, yet efficient modifi-

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cation to the traditional interpolation-based approach to address these shortcomings and compare the performance of our method to a pure linear interpolation approach [7] as well as the novel reprojection-reconstruction approach of Jeong *et al* [14], which is aimed specifically at dealing with images containing multiple metallic objects.

This is the first study to attempt MAR in the context of 3D baggage imagery.

2. 3D CT BAGGAGE IMAGERY

At present there appears to be no MAR-based literature outside of the medical field. It is thus important to emphasise several key differences between the typical medical data and that encountered in a baggage security screening context.

Several state of the art medical CT scanners advertise submillimetre isotropic resolutions in all three dimensions, for example: the Toshiba Medical Aquilion Series CT scanner (isotropic resolution = 0.35mm) [15] and the GE Healthcare Discovery CT750 HD CT scanner (isotropic resolution = 0.23mm) [16].

The volumetric baggage CT data used in this study, however, was obtained using a CT-80 baggage scanner manufactured by Reveal Imaging Inc. and yields an optimal spatial resolution of 1.56x1.61x5.00mm. Furthermore, the primary objective of this scanner is the detection of explosive and organic materials using dual energy CT techniques (as opposed to the objective of medical CT scanners). The demand for a higher scan speed in the security screening setting (compared to the medical setting), leads to compromises in image quality in both resolution and noise [3]. The resolution of baggage data is thus anisotropic and significantly worse than the state of the art medical data (see Figure 1). Anisotropic voxel resolution and poor resolution in the axial plane in particular, compound the effects of image noise and artefacts [6].

Several properties of medical CT images that impact the MAR procedure are worth noting. Prior knowledge regarding the properties of the anatomical region to be scanned exists: for instance it is reasonable to assume that a head CT scan will be composed of brain matter, bone and air. Secondly, theoretical or expected CT values for most anatomical structures exist, making the detection of artefacts (discrepancies in these values), as well as the fine tuning of algorithms (parameter setting) comparatively straightforward [6]. Thirdly, most scans exhibit low degrees of complexity and contain minimal clutter (i.e.they are fairly homogeneous). Finally, most metal objects encountered in medical imaging are fairly small and predictable in nature (size, location, orientation, quantity etc.) [6].

The content of a typical baggage CT scan, on the other hand, is highly unpredictable and often extremely complex, exhibiting high degrees of clutter [17]. Furthermore, the metal objects encountered, especially in the context of this study, are often much larger than those found in the medical setting (e.g. firearm vs. dental filling) and exhibit a much higher degree of variation in their nature. As a result, the metal artefacts generated are generally more severe and extensive. It is widely accepted that both human and computer detection rates are severely affected by complexity and clutter [3].

Therefore, both the origin of the data (scanner type and specifications), as well as the nature of the scanned object, makes the detection and removal of metal artefacts considerably more challenging in the baggage screening setting.

3. PROPOSED ALGORITHM

The vast majority of sinogram completion-based approaches adhere to the following framework: metal segmentation, sinogram completion, final image reconstruction. The algorithm proposed here employs the concept of the virtual sinogram [18] and follows the same general framework with several minor modifications.

Metal segmentation: Metallic objects present in the original reconstructed image are segmented by binary thresholding, yielding a 'metal-only' image. Thresholding exploits the fact that the CT values of metals are extremely high, especially relative to other materials. As is proposed by Jeong *et al* [14], a 'metal-free' image is then constructed by assigning a constant pixel value to the metallic regions in the original, reconstructed image (in this study the mean value of the background (i.e. non-metallic) region of the image is used). This metal-free image is then filtered with the edge preserving non-local means (NLM) filter [19]. The objective of this prefiltering is to reduce weak streaking artefacts and background noise while preserving the non-metallic regions of the image.

Reprojection and sinogram completion: The metal-only image and the filtered, metal-free image are then forward projected using the Radon transform [6], yielding the corresponding virtual sinograms. The metal-only sinogram is used as a mask to reference the corrupted/missing bins in the metal-free sinogram. The affected bins in the metal-free sinogram are then replaced by interpolated estimates from adjacent bins using spline interpolation.

Image reconstruction: The interpolated sinogram is then reconstructed to obtain the corrected, metal-free image. Reconstruction is based on the filtered back projection algorithm which utilises the inverse Radon transform [6]. The metal objects are then reinserted into the interpolated image, yielding the corrected image.

Image refinement: New artefacts introduced by the interpolation process are reduced using the following novel, two step methodology. The pixel values in the corrected image are limited to be less than or equal to the corresponding pixels in the original image. This limit is motivated by the fact that the streaks introduced by the interpolation procedure generally manifest as intense, bright lines affecting the entire image (i.e. not confined to the regions of the original streaking). Regions previously unaffected by streaking, but now affected by the new streaks, thus exhibit higher pixel values. By imposing this upper limit on the corrected pixel values much of the additional streaking is eliminated and what remains is generally very weak streaking. In order to eliminate the remaining weak streaks the image is again filtered with the NLM filter [19], yielding the final artefact-reduced image.

In summary, the proposed algorithm is comprised of the following steps (the novel steps are indicated in bold): - 1) Metal segmentation; 2) Metal removal and NLM filtering; 3) Forward projection and sinogram completion; 4) Image reconstruction; 5) **Limiting of pixel values in reconstructed image**; 6) **NLM filtering**.

4. METHODOLOGY

The performance of the proposed approach (denoted as *MARLimited*) is compared to that of a pure linear interpolation approach [7] (denoted as *MARLinear*) as well as an approach for dealing with multiple metal objects in dental and pelvic scans proposed by Jeong *et al* [14] (denoted as *MARJeong*). To motivate the NLM filtering steps, the results of the proposed approach without filtering are included (denoted as *MARNoFilter*).

The vast majority of MAR studies rely heavily on a subjective analysis for measuring performance. A common trend is to perform both clinical studies using real-world CT scans, as well as simulated studies using phantoms (objects which are designed to mimic the properties of human tissue and/or organs). While the use of simulated studies allows for the establishment of gold standard images and hence the implementation of any standard image reconstruction performance measure [20], only real-world data is used in this study, making such an analysis unfeasible. Furthermore, to the authors'

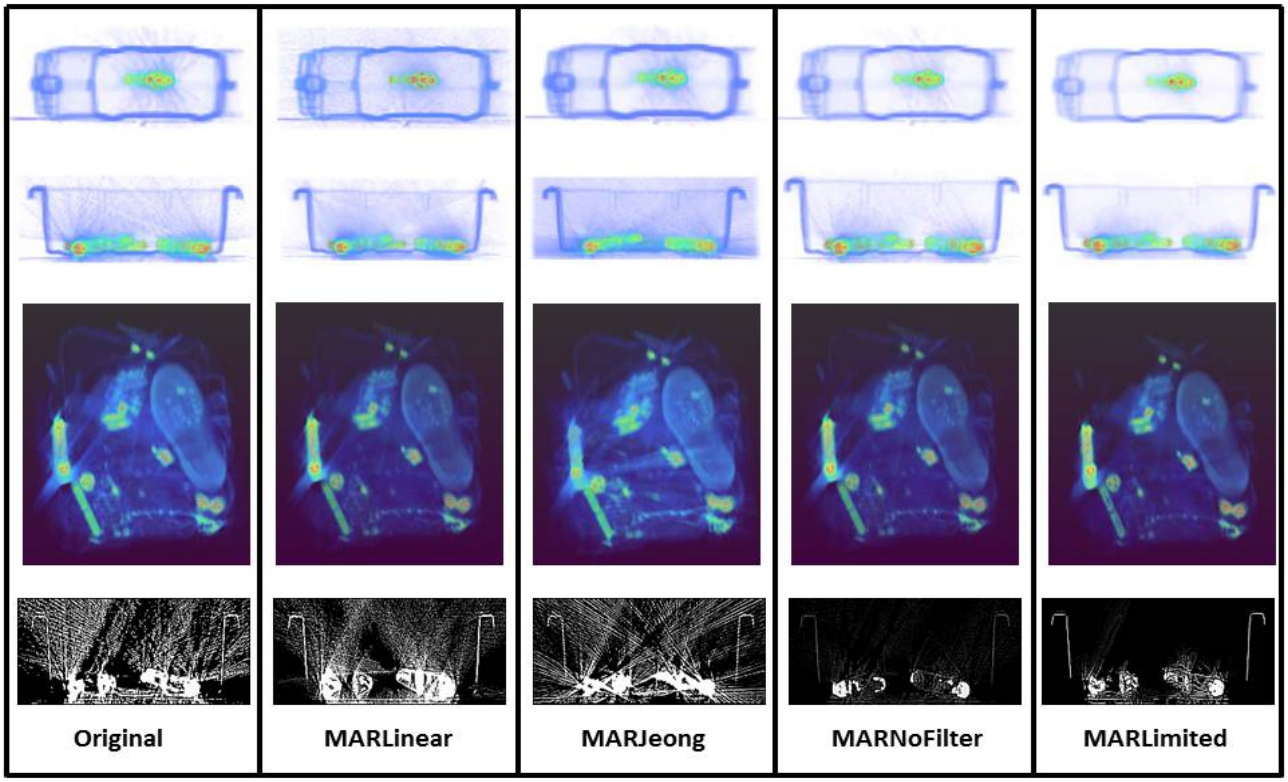

Fig. 2. Visual comparison results.

knowledge, all current MAR studies evaluate performance on a 'per-slice' basis only and do not consider the impact of MAR on the final volumetric image rendering/visualisation [21]. We thus attempt to qualitatively and quantitatively measure performance of the MAR techniques on both the individual slices and the final volumetric images.

Qualitative performance is measured in two ways: the visual quality of the individual CT slices and complete volumes before and after MAR are compared and an iso-surface based volume rendering technique [21] is applied to the data before and after MAR and the visual quality of the resulting volumes compared.

A predominant motivation for effectively removing the artefacts in CT baggage images is to aid the implementation of subsequent automated 3D object recognition. The following, novel technique for quantifying the results of the MAR algorithms is thus introduced: a 3D SIFT point detector [4] is run on the volume before and after MAR and the number of object and noise SIFT points are manually recorded. An object feature point is identified as one located on an object of interest within the CT image whilst a noise feature point is considered as one which is not on the primary object within the CT image (i.e. assumed to be caused by noise or artefacts). The ratio of object feature points to total feature points (object + noise) is used as an indication of the performance of the given technique.

5. RESULTS

The performance of each MAR technique was evaluated on the following three scans obtained from a CT-80 model baggage scanner: a scan of a single metallic object (firearm) in a container with no background clutter; a scan of multiple metallic objects (three firearms) in a container with no background clutter and a scan of a highly cluttered bag containing a single firearm and variety of commonly encountered objects of varying density (e.g. clothing, keys etc.).

Figure 2 shows the volumetric results of applying the three MAR methods to the single firearm (first row), multiple firearms (second row) and cluttered (third row) cases and the results for an individual slice from the multiple firearm case (fourth row) . The first column in the figure displays the original, unprocessed images and subsequent columns display the results of each of the MAR techniques. The streaking artefacts surrounding the firearms in each of the scans are clear in the unprocessed cases.

While MARLinear and MARJeong yielded little to no improvement in visual quality in all three scenarios, MARLimited resulted in a significant reduction in streaking with virtually no new streaking. The final volumes and the individual slice exhibit good preservation of detail and an overall improvement in visual quality. Nonetheless, a noticeable amount of streaking remains in the cluttered image, especially in the lower region of the firearm.

Figure 3 displays the results of the iso-surface based volume rendering algorithm [21] on the original scan and after applying each of the MAR algorithms. While MARLinear yielded no improvement and MARJeong a considerable deterioration, MARLimited resulted in a considerably cleaner result: the surface of the firearm is more homogenous and spurious details around the edges of the firearm have been completely removed.

Finally, Figure 4 displays the results of the novel quantitative analysis discussed earlier. The SIFT point detection algorithm includes a refinement procedure whereby candidate SIFT points are rejected due to poor contrast and/or poor localisation on edges [4]. These rejections are governed by two thresholds which were set according to the optimal values recommended by Flitton *et al* [4]. The number of object and noise SIFT points was manually recorded across three scale-space levels. The results in the table in Figure 4

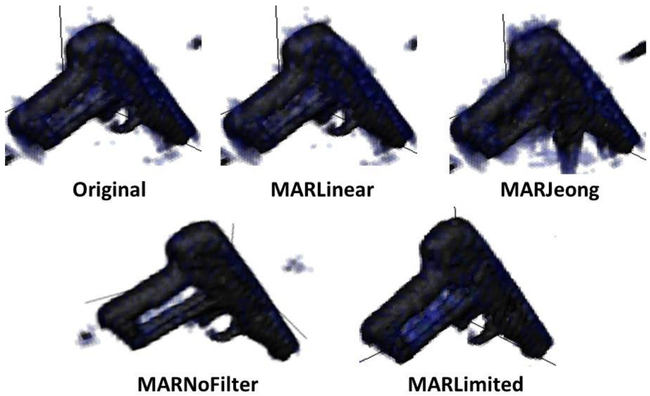

Fig. 3. Volume rendering results.

	Object points	Noise points	Ratio
Original	29	20	0.59
MARLinear	30	12	0.71
MARJeong	27	22	0.55
MARNoFilter	30	7	0.81
MARLimited	**31**	**4**	**0.89**

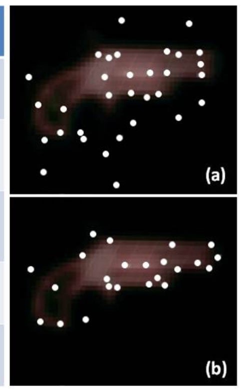

Fig. 4. Quantitative analysis results. Best performing method indicated in bold. SIFT point locations (white dots) before (a) and after applying MARLimited (b).

left indicate that there was no significant variation in the number of object feature points detected for each of the volumes. For the unfiltered volume a total of 20 noise SIFT points was detected, yielding a ratio of object to total feature points of 0.59. MARJeong resulted in a decline in performance (ratio = 0.55) while MARLinear yielded a slight improvement (ratio 0.71). MARLimited (indicated in bold in Figure 4) yielded the optimal results with only 4 noise feature points and a ratio of 0.89: this is a significant improvement over the unprocessed volume as well the other MAR methods evaluated and is a strong indication that MARLimited will lead to improved object recognition results using techniques such as those implemented in [4]. Additionally the SIFT point locations at the first scale-space level on a volume before and after applying MARLimited are shown in Figure 4 right (recall that the values in the table correspond to number of points across all three scale space levels). The unfiltered volume contains 20 object feature points (on the firearm) and 12 noise feature points (in the background), while the filtered volume contains 21 object feature points and 2 noise feature points.

Finally, in all three experiments (Figures 2 - 4), the performance gains yielded by the pre- and post-filtering operations are clear. Note, however, that the proposed approach without filtering still yields considerably better results than the other two methods.

6. CONCLUSIONS

Two novel contributions have been presented: 1) a novel sinogram completion-based technique for MAR in the previously unconsidered context of 3D CT baggage imagery and 2) a novel quantitative analysis technique for quantifying the impact of image restoration techniques on object recognition. The MAR method imposes an upper limit on the processed images and employs a post-filtering operation to reduce the occurrence of new streaking artefacts in the corrected images.

The proposed method was tested on several simple and complex scenarios. Qualitative and quantitative analysis indicated that the proposed approach yielded considerable improvements over a conventional linear interpolation-based approach and a reprojection-reconstruction approach. In particular, the introduction of new streaking in the corrected slices and volumes was almost entirely eliminated. Although these improvements are significant and indicate that the proposed approach will be beneficial to the implementation of automated object recognition, streaking was not entirely eliminated in the most cluttered images; an issue which will be the focus of future work.

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