Partially Lossless Compression of DICOM Image Sets.

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Abstract

In this paper a new approach to the compression of DICOM image sets is presented. For this task, a specific image projection space is created by employing principal component analysis. A subset from the initial image set, which can include regions of interest, is selected and used in the projection space creation. That way, these images can be reconstructed lossless, while the residual images are reconstructed with little loss of information. As shown by conducted experiments, the proposed method yields mean absolute errors below those of linear interpolation methods, yet at the same time achieves evidently higher compression ratios than compared image compression algorithms.

Keywords: Medical imaging, Image compression, ROI, DICOM, PCA.

Introduction

The migration from classical archiving to modern digital Picture Archiving and Communication Systems (PACS) has led to an increased quantity of data that is acquired in a given timespan [1]. The aim is to store this information compactly, simply retrievable, and preferably with little or no loss of quality (thus, using (near-) lossless image compression algorithms). Therefore, various lossless and lossy image compression techniques have been proposed in the past. Some are already included in the Digital Imaging and Communications in Medicine (DICOM) standard [2].

While lossless compression algorithms are employed frequently, the use of lossy compression methods remains limited to some domains (e.g. ultrasound) [3]. The reason for this is primary the insignificant higher compression ratio with regard to the loss of details, which in clinical applications may be critical. For example, lossless compression standards generally yield compression ratios (CR) between 1:2 and 1:3, while lossy compressions achieves CRs between 1:4 and 1:5 [4, 5].

In this paper, we propose a new method for partially lossless compression of whole DICOM image sets instead of compressing each image individually. The method is based on the statistical Principal Component Analysis (PCA) method [6]. By employing PCA for the creation of an image projection space, specific for any given DICOM image set, it is possible to achieve evidently higher CR than using established lossy compression algorithms. To ensure lossless archiving of especially important regions (Regions of Interest (ROI)), specific images from a set can be included in the PCA projection space creation.

Partially lossless compression of DICOM image sets employing PCA

DICOM image sets often contain a large number (up to several hundred) of images. Due to the small inter-slice gaps consecutive images contain similarity visible even on the visual level. This similarity can be understood as between-image redundancy, which can be exploited for image compression. In the presented method, this is achieved by employing PCA.

An adequately exploitable property of PCA, which arises from its mathematical conception, is that images (generally speaking, vectors), which are used for the PCA, can be reconstructed to their original state. In other words, it is possible to specifically select images from ROI, which can be archived lossless. This, however, holds not for the residual images. Thus, the terminus *partially lossless DICOM image set compression*.

Since PCA is a well-established mathematical tool, an in-detail description of the mathematics behind it is omitted. PCA is employed conceptually in the same way as described in [7]. The procedure consists of the following three sub-steps:

- Initially, a DICOM image set $\mathcal{D}$ is acquired. From $\mathcal{D}$, the images, which are going to be used for the creation of the image projection space (the eigenspace), have to be selected. In the presented method, a subset $\mathcal{S}, (\mathcal{S} \subset \mathcal{D})$, was defined to consist of the first image of $\mathcal{D}$ and every *d*-th additional image (e.g., if *d*=5 and $|\mathcal{D}| = 15$, then $\mathcal{S} - \{\mathcal{D}_1, \mathcal{D}_6, \mathcal{D}_{11}\}$). In cases, where specific ROI need to be archived lossless, $\mathcal{S}$ would include the images representing the ROI as well (e.g., $\mathcal{S} = \{\mathcal{D}_1, \mathcal{D}_6, \mathcal{D}_{11}, \dots\} \cup \mathcal{D}_{ROI\,1} \dots \cup \mathcal{D}_{ROI\,n} \mid \mathcal{D}_{ROI\,i} \subset \mathcal{D}$). The described process is illustrated in Figure 1.

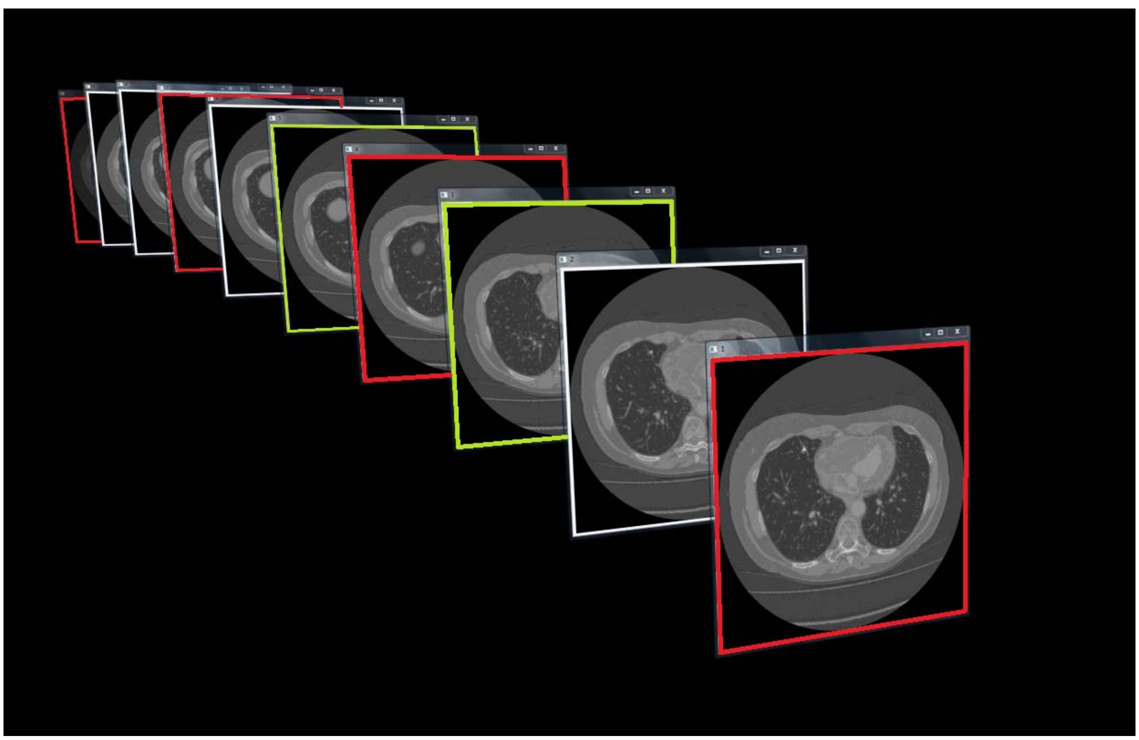


Figure 1: Visualization of the selection process, where the first and every *d*-th (in this case, *d*=3) image is included in *S* (images with red frames). Additionally, images from ROI are included (images with green frames).

- Each image $s_i \in \mathcal{S}$ is transformed to a vector by aligning its rows (or columns). These vectors are gathered in the matrix **S** where each vector stands for one column.

The eigenvectors of the matrix **S** are calculated and again represented in matrix form (denoted by **M**).

- Finally, each image from $\mathcal{D}$ is vectorized, as described above, and projected to the eigenspace by right-hand matrix multiplication by **M**. Each image is now completely represented by the corresponding vector of PCA projection coefficients. These vectors can be restored to images by left-hand matrix multiplication by $\mathbf{M}^{\mathbf{T}}$, where images included in $\mathcal{S}$can be restored to their original form.

The whole DICOM image set is now represented by the matrix **M** and the vectors of PCA projection coefficients. While the archiving procedure involves computationally relatively expensive procedures (the calculation of the eigenvectors of **S**), the retrieving process is straightforward. Thus, the expensive part of the method is performed only once, while image retrieval requires only minimal computational effort.

Results

For testing purposes, the presented method was applied to several distinct DICOM image sets from CT scans. The resolution of all images was 512x512, with a bit-depth of 8 bits/pixel. The results presented in this paper were acquired by compressing an image set of the head (Set 1, consisting of 534 images with 0.5mm inter-slice distance) and an image set of the stomach (Set 2, consisting of 557 images with 1mm inter-slice distance).
Firstly, the quantity of the information loss was estimated. This was measured using the Mean Absolute Error (MAE) metric [8], when using various values for *d*. Therefore, different sets $\mathcal{S}_i, (\mathcal{S}_i \subset \mathcal{D})$ were created and the presented method was applied. For comparison, the image sets were approximated by linear interpolation (which is commonly applied in clinical visualization applications [9]) based on the same datasets.
The results, acquired in the above described experiments, are presented in Table 1, while a graphical representation is given in Figure 2.

	MAE (*d*=5)		**MAE (*d*=10)**		**MAE (*d*=20)**	
	Set 1	Set 2	Set 1	Set 2	Set 1	Set 2
PCA based compression	5.32	3.28	6.71	4.17	7.84	4.94
Linear interpolation	5.57	3.42	10.29	6.52	11.54	7.14

Table 1: Comparison of the proposed PCA based method with linear interpolation in terms of MAE

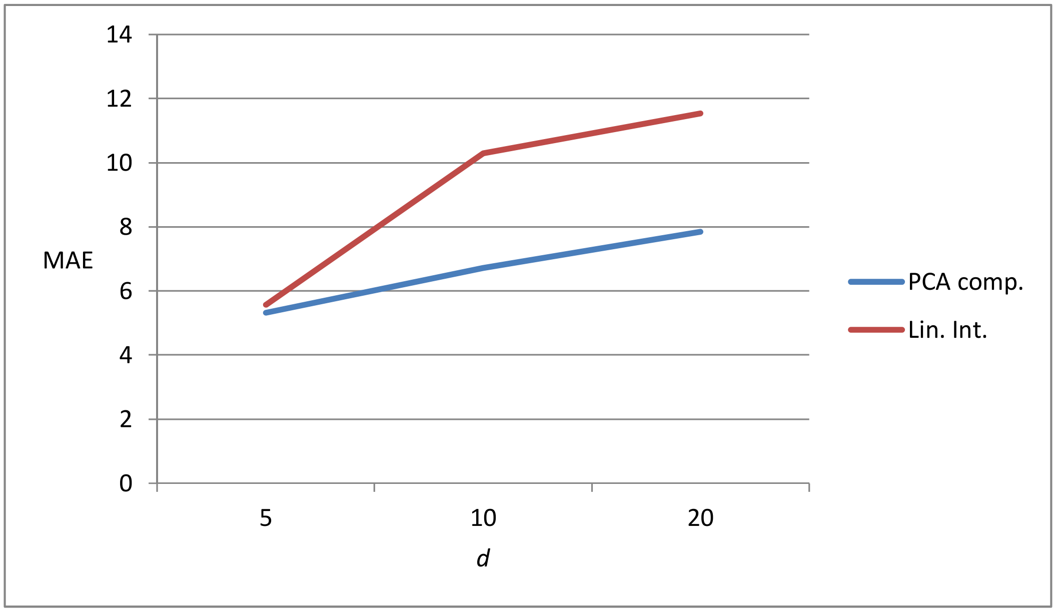
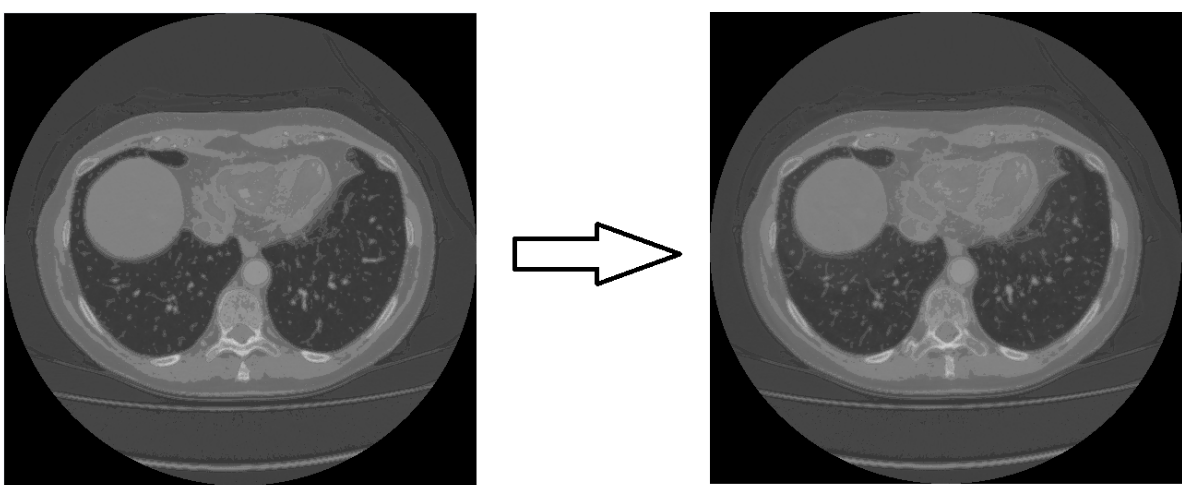


Figure 2: Graphic comparison of the tested methods in terms of MAE (on Set 1).

From the obtained results it is evident that the presented method introduces errors of lower degrees than the commonly applied linear interpolation method.
Figure 3 shows a visual comparison of two lossy compressed images, using the presented method, with their original counterparts.



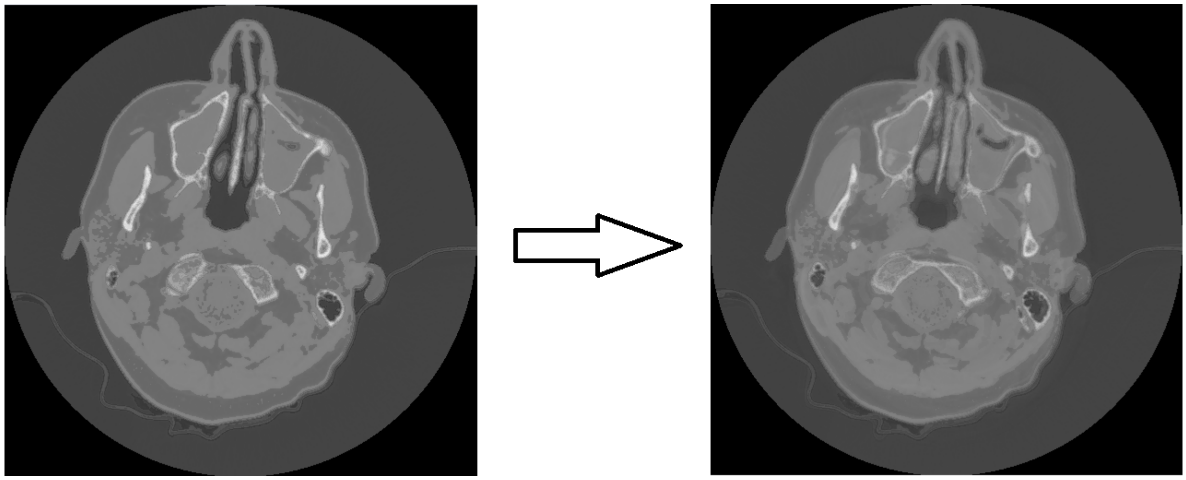


Figure 3: Comparison between two typical original DICOM images (left), and their lossy compressed reconstructions (right). The MAE of the first image is 3.5; the MAE of the second is 3.3.

Further experiments were aimed at determining the achievable CR. For this task, the image datasets were compressed with the presented method using variable values of *d*. Additionally, the same datasets were compressed by lossless (PNG [10]) and lossy (JPEG2000 [11]) compression algorithms (using default quantization parameters) for each image separately. The results of this comparison are presented in Table 2.

The acquired results indicate an evidently higher CR (9.8-times compared to PNG, 3.5-times compared to JPEG2000) achieved by the presented method, even if compared to other lossy image compression standards.

	Original size	**PCA**		**PNG**		**JPEG2000**	
		Set size	CR	Set size	CR	Set size	CR
Set 1	134.16 MB	7.16 MB	1:18.74	70.75 MB	1:1.90	25.08 MB	1:5.35
Set 2	140.09 MB	7.42 MB	1:18.88	72.59 MB	1:1.93	26.19 MB	1:5.35

Table 2: Comparison of the presented method (denoted by PCA, using d=10) with PNG and JPEG2000 in terms of CR.

Conclusion

A new approach to compression of DICOM image sets was introduced in this paper. Instead of archiving each image separately, the between-image similarity (redundancy) was used for the creation of a specific PCA projection space.
By experimental results, it was demonstrated that the proposed method achieves significantly (nearly 10-times) higher compression ratios than compared established methods. At the same time, the introduced error is of lower degree than the error introduced by the common linear interpolation method.
An additional advantage to general lossy compression is the possibility of explicitly selecting lossless regions (images) of interest. The problem of critical information loss, which is the major barrier for the use of lossy image compression in medical applications, is therefore conceptually avoided.

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