Traditional Machine Learning Techniques for Streak Artifact Reduction in Limited Angle Tomography

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Abstract. In this work, the application of traditional machine learning techniques, in the form of regression models based on conventional, "hand-crafted" features, to streak reduction in limited angle tomography is investigated. Specifically, linear regression (LR), multi-layer perceptron (MLP), and reduced-error pruning tree (REPTree) are investigated. When choosing the mean-variation-median (MVM), Laplacian, and Hessian features, REPTree learns streak artifacts best and reaches the smallest root-mean-square error (RMSE) of 29 HU for the Shepp-Logan phantom. Further experiments demonstrate that the MVM and Hessian features complement each other, whereas the Laplacian feature is redundant in the presence of MVM. Preliminary experiments on clinical data suggests that further investigation of clinical applications using REPTree may be worthwhile.

1 Introduction

In computed tomography (CT), image reconstruction from data acquired in an insufficient angular range is called limited angle tomography. It arises when the gantry rotation of a CT system is restricted by other system parts or external obstacles. Because of missing data, artifacts, typically in the form of streaks, will occur in the reconstructed images.

Generally, two main approaches are utilized to deal with the limited angle problem. One is to interpolate/extrapolate the missing data in projection domain [1]. The other is to incorporate prior information into iterative algorithms. Particularly, iterative reconstruction algorithms with total variation (TV) regularization, which exploits sparsity in the image gradient domain, have achieved good performance in limited angle tomography [2,3]. However, iterative algorithms are computationally expensive.

Recently, deep learning has outperformed the state of the art in many computer vision tasks and medical imaing processing tasks as well. The development of techniques such as convolutional neural networks (CNN), often with an encoder-decoder structure, allows to extract intrinsic features from high dimensional data and improves the learning process. Deep learning has proved effective for streak reduction in limited angle tomography [4,5,6]. However, the application of conventional machine learning techniques, i. e., a pixel-by-pixel prediction based on hand-crafted features, in limited angle tomography remains blank in literature. Therefore, in this paper we investigate three regression models in such a setup for limited angle tomography, namely, linear regression (LR), multi-layer perceptron (MLP), and reduced-error pruning tree (REPTree).

2 Materials and Methods

2.1 Input and Output

A general machine learning pipeline includes four main parts: input observations, feature extraction, a classification/regression model, and output labels. In this work, we choose the images reconstructed from the limited angle data (denoted by f_{limited}) as the input.

Gu and Ye [6] point out that streak artifacts are similar to each other even though the artifact-free images are drastically different from each other. They suggest that learning the residual artifact images (denoted by f_{artifact}) is easier than learning the artifact-free images directly. Therefore, in this work we choose the residual artifact images as the output.

2.2 Feature Extraction

Streak artifacts in limited angle tomography appear evidently near object boundaries. They are closely associated with object edges and have certain orientations that are determined by the acquisition geometry. Therefore, the following features are used for streak artifact prediction.

Mean-variation-median (MVM) At each position (x, y), the intensity of $f_{\text{artifact}}(x, y)$ is highly related to the intensity of $f_{\text{limited}}(x, y)$. Therefore, the intensity of $f_{\text{limited}}(x, y)$ is one feature. As it is difficult to predict streak artifacts from a single pixel, the information of its neighborhood is necessary. The neighborhood, typically an image patch, can be characterized by the mean, variance, and median statistic.

Laplacian The Laplacian, or the Laplace operator, is one of the most popular edge detectors. It is a second order differential operator, which is defined as,

$$\Delta f(x, y) = \nabla^2 f(x, y) = \frac{\partial^2 f(x, y)}{\partial x^2} + \frac{\partial^2 f(x, y)}{\partial y^2} \tag{1}$$

Hessian The Hessian matrix is a structure tensor constructed by second-order partial derivatives. It describes the local curvature of an image. The image $f(x, y)$ is first smoothed by a Gaussian kernel $G_s(x, y)$ with a standard deviation s, i. e., $f_s(x, y) = f(x, y) * G_s(x, y)$. The Hessian matrix is computed as,

$$H_s(x, y) = \begin{bmatrix} \frac{\partial^2 f_s(x,y)}{\partial x^2} & \frac{\partial^2 f_s(x,y)}{\partial x \partial y} \\ \frac{\partial^2 f_s(x,y)}{\partial y \partial x} & \frac{\partial^2 f_s(x,y)}{\partial y^2} \end{bmatrix} \tag{2}$$

The two eigenvalues and the orientation of the main eigenvector of $H_s(x, y)$ are chosen as the Hessian features.

2.3 Regression Models

Linear Regression Linear regression is the most popular method in many statistical applications. It expresses the output label as a linear combination of the extracted feature attributes and the trained weights.

Multi-layer Perceptron MLP can learn more complex, nonlinear functions than linear regression. MLP generally contains an input layer, several hidden layers, and an output layer. At hidden layers, nonlinear activation functions like the sigmoid activation function are typically used. The backpropagation method with stochastic gradient descent method is used for training.

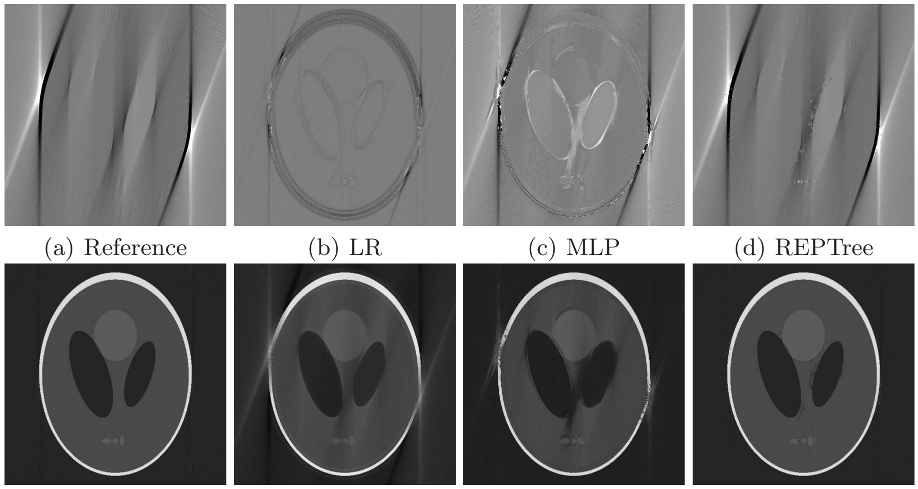
Reduced-Error Pruning Tree A decision tree utilizes a tree-like structure to predict an output from the feature attributes. A tree is learnt recursively by splitting the training data set into subsets based on attribute value tests. The recursion process stops when the subset at a node has all the same value, or the tree reaches the maximum depth. Gini impurity or information gain is typically used to obtain an optimal attribute order for splitting [7]. A pruning process is employed to prevent overfitting. In this paper, we use the reduced-error pruning tree (REPTree) [8] which is a simple and fast pruning method.

2.4 Experimental Set-up

To initially check the validity of different features and regression models, a 3-D standard high-contrast pixelized Shepp-Logan phantom is generated. Its image size is $512 \times 512 \times 200$. The pixel size is 0.4 mm in X and Y directions and 1.024 mm in Z direction. We pick 150 slices from the 3-D volume and one half of them are used for training, the other half for testing. We reproject these images in a parallel-beam geometry using a ray-driven method with a sampling rate of 7.5/mm. No noise is simulated. The scanned angular range is 160°. The angular step is 0.5°. The number of the equal-space detector pixels N_D is 1537 and the detector element size is 0.2 mm.

As preliminary experiments for clinical data, 14 patients' CT data are used, 7 patients for training and another 7 patients for testing. The selected images are reprojected in a fan-beam geometry. The scanned angular range is 170°. The angular increment is 0.5°. The detector has 768 pixels and the pixel size is 0.5 mm. The source to detector distance is $d = 1037$ mm and the fan angle is 20°.

The machine learning algorithms are based on the Waikato Environment for Knowledge Analysis (Weka) [9]. MLP uses four hidden layers. The learning rate, the momentum, and the epochs are set to 0.3, 0.2 and 100, respectively. REPTree sets 1 as the minimum number of instances per leaf node and the maximum depth of the tree is set to be unlimited. The MVM features are extracted from quadratic image patches of side length 2, 4, 8 and 16. For the Hessian features, s is set to 9. The whole implementation is based on CONRAD [10].



(a) Reference (b) LR (c) MLP (d) REPTree

(e) Reference (f) LR, 139.0 HU (g) MLP, 133.4 HU (h) REPTree, 29.3 HU

Fig. 1. Learnt streak artifacts using different machine learning algorithms and their corresponding reconstructed images in parallel-beam with a 160° trajectory. The MVM, Laplacian, and Hessian features are used. The RMSE of images learnt by LR, MLP, and REPTree are shown in the subcaptions (f)-(h). Window width for the top row: 1200 HU; window for the bottom row: [-1400, 1400] HU.

3 Results

The results of different machine learning algorithms using the MVM, Laplacian, and Hessian features for the Shepp-Logan phantom are displayed in Fig. 1. Figs. 1(a)-(d) show that REPTree predicts the artifacts best with only minor misclassifications. By subtracting the learnt streak artifacts, the "destreaked" images are obtained in Figs. 1(f)-(h). While streak artifacts remain in the results of LR and MLP, most of them are reduced by REPTree. The root-mean-square errors (RMSE) of the destreaked images w. r. t. the image reconstructed from full data (Fig. 1(e)) is further computed. REPTree reaches the smallest RMSE value of 29.3 HU.

To investigate the effects of different features in streak artifact classification, the results of REPTree using different combinations of features for the Shepp-Logan data are shown in Fig. 2. Figs. 2(a)-(c) indicate that using MVM only is able to predict most streak artifacts while using Laplacian or Hessian only is not sufficient. Comparing Fig. 2(d) with Fig. 2(a), the Laplacian feature is redundant in the presence of MVM since Fig. 2(d) and Fig. 2(a) have almost the same image quality. Fig. 2(e) and Fig. 1(h) also demonstrate this. Fig. 2(e) indicates that the Hessian features are beneficial, compared with Fig. 2(a).

The preliminary experiments on the clinical data are displayed in Fig. 3. Figs. 3(c) and (f) demonstrate that REPTree reduces most streak artifacts well. However, it misclassifies some normal tissue as streak artifacts.

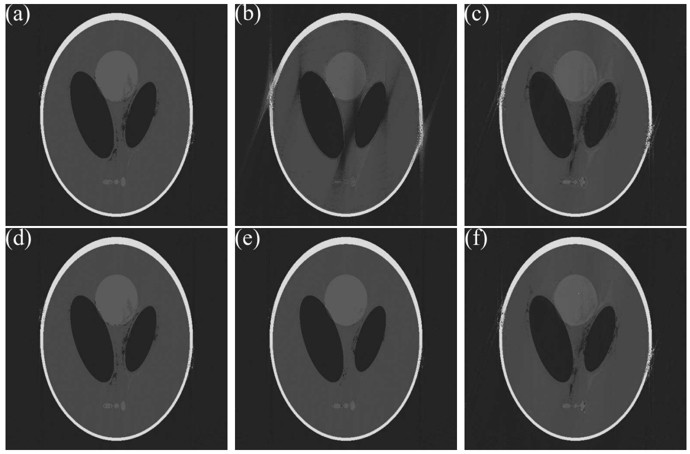


Fig. 2. The results of REPTree using different feature combinations in parallel-beam with a 160° trajectory: (a) MVM, (RMSE =) 38.4 HU; (b) Laplacian, 119.2 HU; (c) Hessian, 76.48 HU; (d) MVM and Laplacian, 38.5 HU; (e) MVM and Hessian, 28.9 HU; (f) Laplacian and Hessian, 65.0 HU. Window: [-1400, 1400] HU.

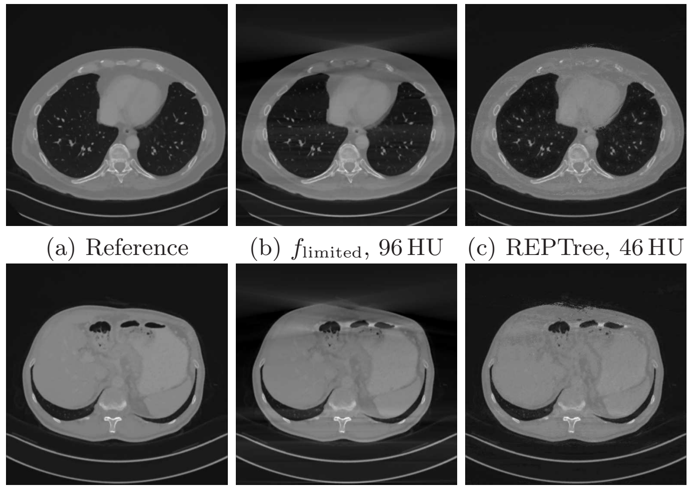
4 Discussion

The mapping from the selected feature attributes to the streak artifacts is a complex nonlinear function. Therefore, LR fails to model that. Although a large MLP with enough hidden units can model any nonlinear functions, in our case, MLP fails to find the desired function during training. REPTree represents the mapping function well with enough nodes and it reduces the overfitting problem with pruning. Therefore, REPTree performs best in the experiments (Fig. 1).

The Laplacian feature is redundant in the presence of MVM (Fig. 2). As a potential reason, one has to consider that the Laplacian is just a linear combination of the neighboring pixels described by MVM. The Hessian features are beneficial since they stress on the strength as well as the orientation of local curvatures, which are essential properties of limited angle streak artifacts.

In summary, we investigate the application of LR, MLP, and REPTree for streak artifact reduction in limited angle tomography. The experiments on the Shepp-Logan phantom demonstrate that REPTree has the best performance on learning streak artifacts compared with LR and MLP. They also indicate that MVM and Hessian features are beneficial for streak artifact prediction while the Laplacian is redundant in the presence of MVM. The preliminary experiments on clinical data suggests that further investigation of clinical applications using REPTree may be worthwhile.

Disclaimer: The concepts and information presented in this paper are based on research and are not commercially available.



(a) Reference (b) f_{limited}, 96 HU (c) REPTree, 46 HU

(d) Reference (e) f_{limited}, 113 HU (f) REPTree, 58 HU

Fig. 3. The reference images, the limited angle reconstructions (denoted by f_{limited}), and the machine learning results using REPTree with the MVM and Hessian features of two clinical datasets in fan-beam with a 170° trajectory. Window: [-1150, 1300] HU.

References

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