33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

A Correlation and LS-SVM based approach to Mitigate Motion Artifacts in FDK Based 3D Cone-beam Tomography

Ujjal Kumar Bhowmik, Reza R. Adhami
Department of Electrical and Computer Engineering
The University of Alabama in Huntsville
Huntsville, AL-35899, USA
Emails: ukb0001@uah.edu, rradhami@eng.uah.edu

Abstract— **Head motion during brain CT studies can degrade the reconstructed image by introducing distortion and loss of resolution, thereby contributing to misdiagnosis of diseases. In this paper, we have proposed a correlation coefficient and Least Squares Support Vector Machines (LS-SVM) based approach to detect and mitigate motion artifacts in FDK based three-dimensional cone-beam tomography. Motion is detected using correlation between adjacent x-ray projections. Artifacts, caused by motion, are mitigated either by replacing motion corrupted projections with their counterpart 180° apart projections under certain conditions, or by estimating motion corrupted projections using LS-SVM based time series prediction. The method has been evaluated on 3D Shepp-Logan phantom. Simulation results validate our claims.**

Keywords- **Three-dimensional CT, Motion Detection, Motion Artifacts, FDK, LS-SVM, Time series prediction.**

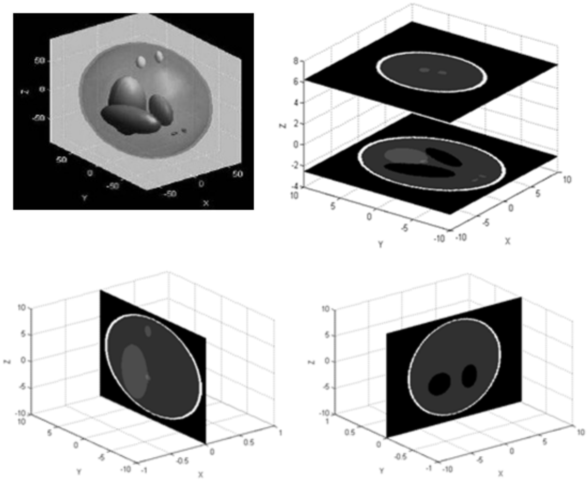
I. INTRODUCTION

Patient head movement remains as one of the significant source of problems in most of the brain CT (computer tomography) applications. It is essential that the head being imaged remain still during x-ray data acquisition process. However, patient movement has frequently been reported in clinical applications. Even with substantial head restraint, some amount of head motion is likely to occur, especially in less cooperative patient like children[1]. Patient motion can adversely affect the reconstructed image through distortion and other artifacts such as blurring and doubling, thereby losing substantial information, which ultimately affects the diagnosis of diseases. Therefore, it is imperative to mitigate or to even eliminate motion artifacts for diagnostic purposes.

Over the past few years several methods have been developed to detect and correct motion artifacts. Most of these techniques are based on using external sensors to detect and quantify head motion and then using motion parameters in the 3D reconstruction. Goldstein et al. [1] proposed a device uses a triad of three incandescent lights affixed on patient's head while viewed by two position sensitive detectors. Fulton et al. and Beache et al. [2] also proposed similar approach that uses infrared reflector and detector. On the other hand, several other approaches solely based on image data themselves, such as a motion correction method based on cross-correlation of summed horizontal and vertical sinogram of successive projection, a motion estimation based upon a parabolic fitting of the peak of correlation function of the sinogram/linograms of projections, have been reported in the literature. It must be noted that motion detection using external sensor could cause systematic biases in the reconstructed images. Therefore, without using any extra sensor we propose an image data based approach to detect and mitigate motion artifacts. Unlike using only sinogram/linogram information of projection to detect motion and estimate correction, which often fail in case of substantial motion, we use the correlation-coefficient of adjacent x-ray projections to detect and locate motion. Once the place of the motion is detected, we either replace the motion corrupted projections by their corresponding 180° apart counterparts projection or estimate projections using time series prediction to replace motion corrupted projection, depending on the location of the motion. The proposed method uses the OSCaR-02 [3] implementation steps for FDK based 3D reconstruction. In this paper, we have used modified form of X-ray projection equation of [2] to incorporate all possible motions, rotation and translation, of the 3D Sheep-Logan phantom. Simulation results verify the accuracy of our proposed method.

II. SIMULATIING MOTION CORRUPTED 3D RECONSTRUCTION

A three-dimensional version of the shepp-logan phantom is considered as the commonly used simulation model in 3D-Computer Tomography (CT) imaging reconstruction field. In this paper the 3D Shepp-Logan model of Fig.1 is adopted for our simulations. The model consists of ten superimposed ellipsoids with different attenuation coefficients (CT values). The geometric locations, sizes and CT values of the ellipsoid used in the model are listed in Table 1[2]. CT value of water and air is 0 and -1000Hu respectively, while that of the bone varies from +100 to more than +1000. In our simulation, the CT values of the ellipsoids were choosen to smulate the soft tissue, bone and other matters located in the head.



a b c d Figure 1. (a) A three-dimensional version of the Shepp-Logan head phantom. (b) Axial slices of the phantom at Z=-2.5cm and 6.25cm. (c) & (d) Sagittal and Coronal slices of the phantom at X=0 and Y=0 positions respectively.

Table 1 Parameters of 3D Shepp-Logan Model

Center Coordinate (cm)			Half axis (cm)			Rotation angle			CT Value
x_o	y_o	z_o	a	b	c	φ	ψ	ξ	ρ
0	0	0	6.90	9.20	9.00	0	0	0	1000
0	0	0	6.62	8.74	8.80	0	0	0	-800
-2.2	0	-2.5	4.10	1.60	2.10	108	0	0	-200
2.2	0	-2.5	3.10	1.10	2.20	72	0	0	-200
0	3.5	-2.5	2.10	2.50	5.00	0	0	0	100
0	1.0	-2.5	0.46	0.46	0.46	0	0	0	100
-0.8	-6.5	-2.5	0.46	0.23	0.20	0	0	0	100
0.6	-6.5	-2.5	0.46	0.23	0.20	90	0	0	100
0.6	-1.05	6.25	0.56	0.40	1.00	90	0	0	100
0	1.0	6.25	0.56	0.56	1.00	0	0	0	100

The x-ray projection of an ellipsoid, *E*, is the length of the line segment going through *E* multiplied by the CT number *(ρ)* of that ellipsoid. According to the linearity of the radon transform, a projection of an object consisting of ellipsoids is just the sum of the projections of each individual ellipsoid. As listed in Table 1, the description of an ellipsoid, *E,* can be obtained by rotations, φ, ψ and ξ, about *z, y* and *x* axis respectively and translation from the origin to the (x_o, y_o, z_o) position.

In circular cone-beam CT system the source-detector pair is rotated in a circular orbit about z-axis by angle β, where β varies from 0 to 360 degree with a suitable step size, w.r.t. x-axis and the ray integrals, projections, are measured on the detector plane as shown in Figure 2. Using Parametric form of projection equation, and six motion parameters, we simulated several gradual motions during X-ray acquisition time. Three different types of motions (translational, rotational, and rotational & translational combined) applied to the 3D Phantom are listed in Tables 2, 3 and 4.

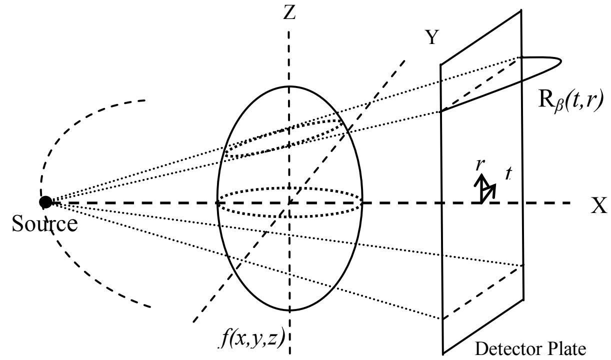


Figure 2

The FDK algorithm is the most widely used algorithm for cone-beam volume reconstruction. In practice, the cone-beam data acquired by the flat panel detector are row-wisely filtered with a suitable reconstruction filter and followed by a 3D back projection for volume reconstruction. In this paper, we adopt the OSCaR-02 [3] implementation for efficient FDK based cone-beam reconstruction. Some of the images of motion corrupted projections and the axial, coronal and sagittal slices of the reconstructed volume of these cases are plotted in Figures 3, 4 and 5.

Table 2. Translational motion given to the Phantom during scanning of projections at 260°, 270°, and 280°

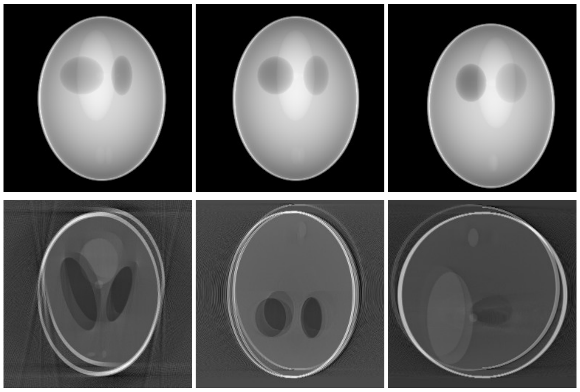
Step	Roll	Pitch	Yaw	x_o(cm)	y_o(cm)	z_o(cm)
260	0°	0°	0°	0.4	0	0
270	0°	0°	0°	0.6	0.6	0
280	0°	0°	0°	0.8	0.8	0.8

Table 3. Rotational motion given to the Phantom during scanning of projections at 260°, 270°, and 280°

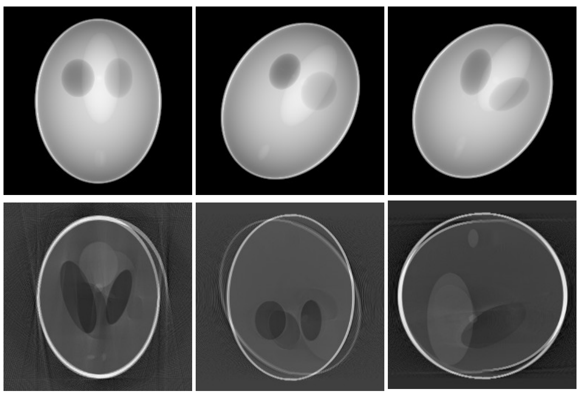
Step	Roll	Pitch	Yaw	x_o(cm)	y_o(cm)	z_o(cm)
260	15°	0°	0°	0	0	0
270	15°	30°	0°	0	0	0
280	15°	30°	25°	0	0	0

Table 4. Combined Rotational and Translational motion given to the Phantom during scanning of projections at 160°, 180°, and 200°

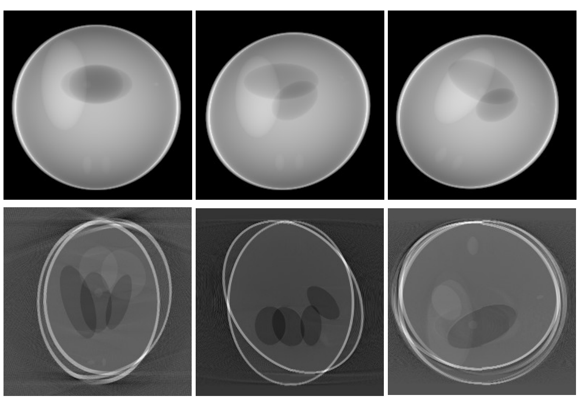
Step	Roll	Pitch	Yaw	x_o(cm)	y_o(cm)	z_o(cm)
160	15°	0°	0°	0.2	0.2	0.2
180	15°	30°	0°	0.4	0.4	0.4
200	15°	30°	25°	0.6	0.6	0.6



a b c
d e f Figure 3 (a-c) Projections at 260°, 270° and 280° source positions. (d-f) Axial, coronal and sagittal slices of the translational motion corrupted reconstructed volume.



a b c
d e f Figure 4. (a-c) Projection at 260°, 270° and 280° source position. (d-f) Axial, coronal and sagittal slices of the rotational motion corrupted reconstructed volume.



a b c
d e f Figure 5. (a-c) Projection at 160°, 180° and 200° source position. (d-f) Axial, coronal and sagittal slices of the translational and rotational motion corrupted reconstructed volume.

III. Motion Detection and Mitigation

The idea behind our motion detection originated from the fact that the information content of two adjacent projections, which are taken 1° apart source positions, are almost similar. So the value of the correlation-coefficient between adjacent projections will be very high. If the object under investigation suffers from any kind of motion, then the value of the correlation-coefficients of some of the adjacent projections will drop from the normal values depending upon the amount and position of the motion. Using the following Equation, we calculated the correlation-coefficients for motion free case, and the above three motion corrupted cases. Figure 6, the plots of correlation-coefficient (Cc) of these four different cases, validates our assumption.

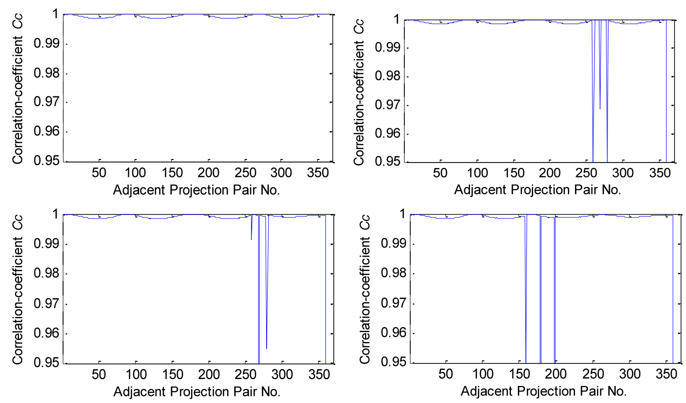
$$Cc = \frac{\sum_m \sum_n (A_{mn} - \bar{A})\,(B_{mn} - \bar{B})}{\sqrt{[\sum_m \sum_n (A_{mn} - \bar{A})^2][\sum_m \sum_n (B_{mn} - \bar{B})^2]}}$$

Where,

m, n are the pixel position.

$A_{mn} = R_\beta(t, r)$ and $B_{mn} = R_{\beta+1}(t, r)$

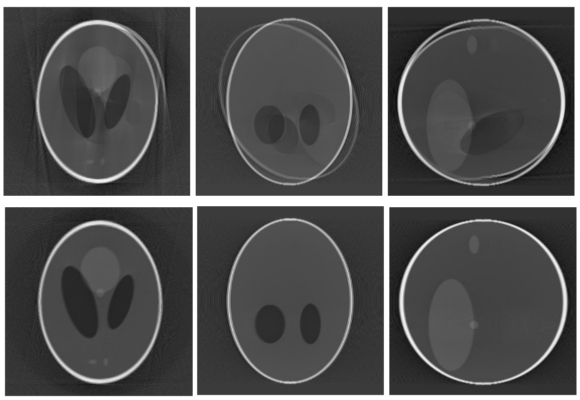
$\bar{A}$ and $\bar{B}$ are the mean of A and B respectively



a b
c d Figure 6. Correlation between adjacent projections. (a) Without motion. (b) For translation motion. (c) For rotational motion (d) Combined rotational and translational case.

From the above plots it is evident that the motion and the position of the source detector pair, where the motion occurs, can easily be identified by comparing the correlation-coefficient values.

Once motion corrupted projections are identified, they are replaced by their counterpart projections, which are 180 apart, to get rid of the motion artifacts in the reconstructed volume. Let us consider the rotational motion case first. It can be seen from Fig. 6(c) that the motion corruption occurs at source detector pair positions, β = 260°, 270°, and 280° and starting from β = 1° to 259° positions the object under investigation remain stable. So, in order to remove motion artifacts from the reconstruction we need to replace the projections at β = 260° to 360° positions with their counterpart projections at β = 80° to 180° positions. But before we do that we need to flip over the information content of every projection of β = 80° to 180° positions from left to right. After all the projections are aligned we applied the OScAR-02 implementation steps to reconstruct 3D volume of the object. We applied the same technique for the other motion corrupted case. In Fig. 7 shows the plots of axial, coronal and sagittal slices of reconstructed volume of rotational motion corrupted case. However, this method does not work if motions occur near β =180°. As for example, the combined translational and rotational motion case, in which motions occur at source positions 160° to 200° positions, i.e. in both half circles of the scanning position, then the 180° apart projections of the projections near β =180° position are not counterpart- In that case, we need to estimate the motion corrupted projections near β =180° positions. For our particular case we need to estimate the projections at β =160° to β =180° positions to get artifacts free reconstruction. Of course, the quality of the reconstructed image will be dependent on how better we can estimate those motion corrupted projections. Here, we have used LS-SVM based time series prediction of every pixels of the motion corrupted projections from the pixels of previous projections at β =1° to β =159° positions.



a b c
d e f Figure 7. (a-c) Axial, coronal and sagittal slices of the rotational motion corrupted case. (d-f) same slices after motion compensation.

IV. Prediction Approach

We want to predict the sequence of future pixel values X_{t+1}^{t+h} from given time series of pixels X_1^t. A training data set is created using a sliding window of length *p*+*h*. Each instances of the sliding window corresponds to a record in the training set. For example, the first record of the training set contains $X = [x_1, x_2, \ldots x_p]$ as its input variables and $Y = [x_{p+1}, x_{p+2}, \ldots x_{p+h}]$ as its output variables. Similarly, the second record contains $X = [x_2, x_3, \ldots x_{p+1}]$ as its input variable and $Y = [x_{p+2}, x_{p+3}, \ldots x_{p+h+1}]$ as its output variables, while the last record contains $X = [x_{t-h+p+1}, x_{t-h+p+2}, \ldots x_{t-h}]$ as its input variables and $Y = [x_{t-h+1}, x_{t-h+2}, \ldots x_t]$ as its output variables. The size of the prediction window *h* is domain dependent and depends on the nature of the application. Akike's final prediction error [4] has been used for determining the order of *p*. For our particular case we used *h*=100 and *p* =12. We first predict x_{t+1} using the previous *p* values, $x_{t+1-P}, \ldots, x_{t-1}, x_t$. we then predict x_{t+2} based on its previous *p* values, which includes the predicted values for x_{t+1}. The procedure is repeated until the last value, x_{t+h}, has been estimated. Figure 8. shows the two intensity profiles of pixels at position (100, 125) for original and predicted projections at β =161° to β =260° positions. From the figure it is evident that our LS-SVM predictor does a very good work for the first 40 values. It gives us the primary indication of how many projections can be estimated within acceptable range of error. Fig. 9 shows two axial slices of the reconstructed volume of above motion corrupted case and estimated projection case.

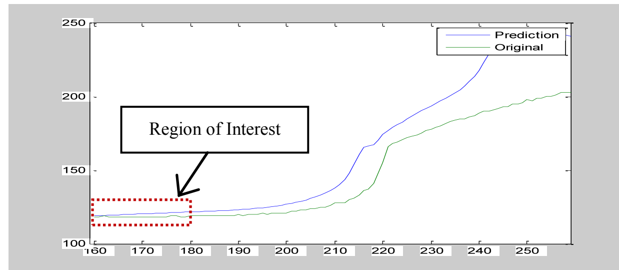


Figure 8. Intensity profile of pixels at (100,125) position.

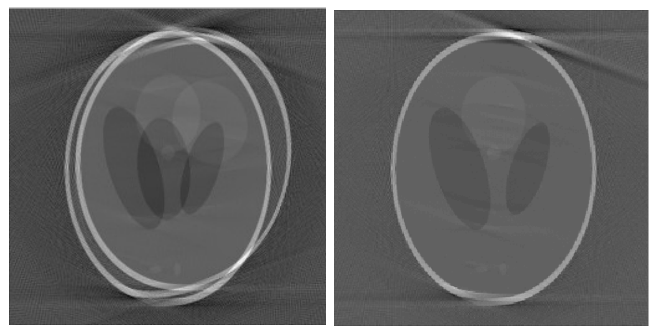


Figure 9. Axial slices of reconstructed volume of motion corrupted case and estimated projection case.

V. Conclusion

We have designed and implemented a correlation and SL-SVM based technique to detect and compensate motion artifacts in FDK based three-dimensional computer tomography. Simulation results validate our claims for motion detection and artifacts mitigation. In our future research, efforts will be made to improve the performance of the estimator, and apply our method to real life data set.

References

[1] R. Goldstein, E. Margaret, and W. Dube, "A Head Motion Measurement System Suitable for Emission Computed Tomography," *IEEE Trans. Of Medical Imaging,* Vol. 16, No. 1, pp 17-27, February 1997.

[2] U. Bhowmik, S. Aravetti, R. Adhami, "An Innovative Approach to Reduce Streaking Artifacts in FDK Based 3D Cone-beam Tomography" *IEEE Southeastcon 2011.*

[3] N. Rezvani, D. Arullah, K. Jackson, D. Mosley and J. Siewerdsen, "An Open Source Cone-Beam CT Reconstruction Tool for Imaging Research," Poster *AAPM,* 2007.

[4] Haibin Cheng, Pang-Ning Tan, Jing Gao, and Jerry Scripps *Multi-step Ahead Time Series Prediction,* Proc of the Tenth Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD'06), 2006.