Comparison of data-driven respiratory signal extraction methods from cone-beam CT (CBCT)

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Abstract. In Cone-Beam CT (CBCT) imaging, respiratory motion needs to be considered to mitigate motion artifacts thus increasing the accuracy of reconstructed images. Data driven methods can be used to extract respiratory signal directly from projection data without requiring any additional equipment or surrogate devices. Digital phantoms provide an adequate option to evaluate developing methods prior to clinical implementation. In this study, four data driven methods are used to extract respiratory signal from simulated projections. An in-house 4D MRI-based CBCT digital phantom is used, where actual respiratory signal is available as ground truth. In comparing all four data driven methods, the respiratory signal extracted using the Local Principal Component Analysis (LPCA) method is found to be robust and yielded the highest correlation coefficient of 0.8644 compared to the ground truth.

1. Introduction
Internal motion such as respiration is inevitable during cone-beam CT (CBCT) imaging such as in image guided radiotherapy (IGRT). Current intrafraction radiotherapy treatment delivery protocols include a 1-minute period to acquire a 3D CBCT scan during which on average, 12 respiratory cycles can occur. Thus the reconstructed images are heavily degraded due to motion artifacts.

Sophisticated algorithms with accurate reconstruction can be achieved when motion tracking is included in its development [1]. These algorithms often rely on respiratory signals which are extracted directly from the projection data. The Amsterdam Shroud (AS) [2], Intensity Analysis (IA) [3], Local Principal Component Analysis (LPCA) [4], and Fourier Transform (FT)-based [5] methods are examples of data driven methods used to extract respiratory signal directly from projection data acquired during the 1-minute scan.

Recently, an in-house digital phantom from actual 4D Magnetic Resonance Imaging (MRI) datasets to simulate CBCT image acquisition was developed [6]. The advantage of using a digital phantom is the availability of ground truth. The accuracy and robustness of each method to extract respiratory motion from simulated projections can be evaluated since the actual respiratory motion of the digital phantom is available. In this paper, the 4 methods above are evaluated using the digital phantom.

2. Materials and Methods
There are 2 stages in this study: 4D CBCT simulation and respiratory signal extraction which are described separately below.
2.1. 4D CBCT simulation
Figure 1(a) shows the geometry used to simulate the Varian On-Board Imager: CBCT Half-Fan operating mode for a standard thoracic protocol. The digital phantom used is the recently developed MRI-based CBCT phantom [6]. An example projection at view angle, $\theta = 0^\circ$ is shown in Figure 1(b).

![Figure 1. (a) Geometry used for CBCT simulation, (b) example projection at $\theta = 0^\circ$](image1.png)

2.2. Respiratory signal extraction
Figure 2 shows a flowchart of the overall methodology to extract the respiratory signals from the simulated CBCT acquisition. The first 3 methods considered are based on a 2D Amsterdam Shroud (AS) image as shown in Figure 3 below. There is a fourth method category: the Fourier Transform based methods, which do not rely on the AS image.

![Figure 2. A flowchart of the methodology used in this study](image2.png)

![Figure 3. 2D Amsterdam Shroud (AS) image](image3.png)
2.2.1. Amsterdam Shroud (AS) method [2]. Being one of the earliest data driven methods introduced, the AS image is first generated by summing the edge-enhanced projection attenuation intensity along the lateral detector direction and concatenating the summed columns into a 2D image, as shown in Figure 3. Using the L2-minimization criterion, shifted pairs of consecutive columns are evaluated across the AS image to extract the 1D signal. A band pass filter is then required to distinguish the desired respiratory signal from other motions.

2.2.2. Intensity Analysis (IA) method [3]. The IA method extends the AS method by proceeding to sum the attenuation intensities along the vertical direction of the AS image. A similar band pass filter is then used to extract the respiratory signal.

2.2.3. Local Principal Component Analysis (LPCA) method [4]. In this study, the LPCA method used differs from the approaches proposed by [4]. Instead of pre-processing the AS image, the sliding window is directly applied to the same AS image used in the other data driven methods.

2.2.4. Fourier Transform (FT)-based method [5]. There are two FT-based methods, namely: FT-magnitude and FT-phase methods. These methods stem when performing Fourier Transform on the edge-enhanced 2D projection dataset. Both methods use a band pass filter to extract the respiratory signal, with the latter requiring an additional phase determination step.

3. Results and Discussion

Each of the extracted respiratory signals is evaluated qualitatively using the ground truth obtained from the actual respiratory signal of the digital phantom, via determining the voxel variation of both segmented lungs throughout the 1-minute scan. The plots are shown in Figure 4. Quantitatively, the correlation coefficients of the extracted signals from each data driven method with the ground truth is also evaluated. The correlation coefficients values are tabulated in Table 1.

![Figure 4](image-url)

**Figure 4.** Extracted respiratory signals, compared with (a) the ground truth, using (b) AS method, (c) IA method, (d) LPCA method, (e) FT-m method, and (f) FT-p method.
Table 1. The correlated coefficient values between extracted respiratory signals and ground truth

| Method                                   | Correlation coefficient |
|------------------------------------------|-------------------------|
| Amsterdam Shroud (AS)                    | 0.7534                  |
| Intensity Analysis (IA)                  | 0.6950                  |
| Local Principal Component Analysis (LPCA)| 0.8644                  |
| Fourier Transform-magnitude (FT-m)       | 0.6950                  |
| Fourier Transform-phase (FT-p)           | 0.8066                  |

Generally, all of the extracted respiratory signals using the data driven methods used in this study are “in-phase” with the ground truth. This encourages the usability of these methods to track internal motion from the acquired projection data during CBCT without any additional equipment.

The signal extracted using the AS method in Figure 4(b) displayed a minimal correlation within the view angle ranging between 90° to approximately −45°. This may be due to the dependency of the AS method to the diaphragm-structures that needs to be apparent within each projection view [7].

The IA method yields a signal in Figure 4(c) that correlates well near view angles positioned laterally parallel to the patient. The same signal is reproduced by the FT-m method shown in Figure 4(e), with the same minimal correlation coefficient value [4]. The other Fourier Transform based method, FT-p method in Figure 4(f) on the other hand, yields a signal with a relatively higher correlation value, but in the expense of an additional post-processing phase determination step.

The LPCA method in Figure 4(d) yields the highest correlation value with the ground truth. The LPCA method here excludes the original pre-processing step of removing the foreground features of the AS image as suggested in [4], and not applying the sliding window to a region of interest as introduced in an improved version recently in [8], therefore displaying its robustness.

4. Conclusions
Four data driven methods have successfully extracted respiratory signals from simulated projection data of a 4D digital phantom that was recently developed. The LPCA method displayed robust performance and yielded accurate results i.e. highest correlation with the ground truth signal.

5. References
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