Quantication and analysis of respiratory motion from 4D MRI

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Abstract. It is well known that respiratory motion affects image acquisition and also external beam radiotherapy (EBRT) treatment planning and delivery. However often the existing approaches for respiratory motion management are based on a generic view of respiratory motion such as the general movement of organ, tissue or fiducials. This paper thus aims to present a more in depth analysis of respiratory motion based on 4D MRI for further integration into motion correction in image acquisition or image based EBRT. Internal and external motion was first analysed separately, on a per-organ basis for internal motion. Principal component analysis (PCA) was then performed on the internal and external motion vectors separately and the relationship between the two PCA spaces was analysed. The motion extracted from 4D MRI on general was found to be consistent with what has been reported in literature.

1. Introduction
It is well known that respiratory motion affects image acquisition and also external beam radiotherapy (EBRT) treatment planning and delivery [1]. Many approaches to manage respiratory motion are also known and researched. The method of motion compensation or corrections depends on the assumption of the corrupting motion. Often the existing approaches are based on a generic view of respiratory motion such as the general movement of organ, tissue or fiducials [2]. More recently there has been interest in using dynamic volumetric imaging such as 4D MRI for more accurate quantification of motion. There have also been recent studies aiming to generate 4D CT from 4D MRI with the indented benefit of less ionising radiation and capability of capturing variability in motion [3, 4]. However, analysis based on 4D MRI may still describe respiratory motion in a rather generic way [5]. This paper builds on previous work [6, 7], aiming to present a more in depth analysis of respiratory motion based on 4D MRI for further integration into motion correction in image acquisition or image based EBRT.

2. Methodology
An open access 4D MRI dataset [8] was used to obtain respiratory motion for five volunteers. As described in [8], the data was acquired using a 1.5 T Philips Achieva™ scanner with a 32-channel coil. The temporal resolution was 0.7 s per volume, with each volume having a dimension of 336 × 45 × 336 voxels and a voxel size of 1.48214 × 5.5 × 1.48214 mm³. For this paper, only the motion for the first volunteer was analysed as a proof of concept of the methodology.

For a more detailed analysis of the motion to be found, the major organs were delineated using a semi-automated segmentation procedure as in [6]. The segmented organs are the lungs, heart, liver,
spleen, stomach and kidneys. The major airways i.e. trachea and primary bronchi, was also segmented. The respiratory system itself was segmented using a more automated procedure as described in [9]. The resulting segmentation is shown in Figure 1 using ITK-SNAP.

![Image of Figure 1](image.png)

**Figure 1.** Display of slices in three orthogonal planes with a rendering of the segmented anatomy (lower left) in ITK-SNAP. The rendered anatomy are the lungs (blue), heart (red), liver (magenta), stomach (peach), spleen (cyan), kidneys (dark red), major airways (dark blue) as well as the body (yellow).

Respiratory motion was extracted using a free form deformation based image registration i.e. the NiftyReg registration package [10, 11]. The default NiftyReg parameter values were used and sum of square differences was used as the registration basis. The motion was calculated for each voxel of the image as well as averaged values found per organ. Motion was quantified as a vector in the image coordinate system (superior-inferior (SI), anterior-posterior (AP), left-right (LR), referred to hereafter as the z-, y- and x-axes) as well as in terms of magnitude of the motion vector.

Additionally, motion of the anterior surface of the body was also found using the procedure described in [7]. This ensures that the motion can be found to sub-voxel accuracy as well as using a different method than the one used for extracting internal motion. The purpose of detecting surface motion serves as a simulation of motion detected from a markerless camera surrogate, such as the VisionRT system. The correspondence between internal and external motion is also analysed as was performed in [7].

3. **Analysis and results**

In this section, the internal and external motion was analysed separately as well as the correlation between them in subsections 3.1 and 3.2 respectively.

3.1. **Internal and External Motion**

As in [6], internal motion was quantified in the x-, y- and z-axes on a per-organ basis as well as over all major organs. Additionally the average magnitude was found over all organs. This is shown in Figures 2(a) and (b). The error bars signify the standard deviation.
(a) Maximum component displacement for each organ.

(b) Maximum displacement over all organs.

Figure 2. Analysis of the mean trajectory of all voxels in the chosen organs. The labels of the chosen organs are: RL: right lung, LL: left lung, MjA: major airways, Hrt: heart, Lvr: liver, Stm: Stomach, Spl: spleen, RK: right kidney and LK: left kidney.

From Figure 2(a), it can be seen that in general, the proportion of motion between the three orthogonal directions are as expected, i.e. larger in the z-axis (SI motion). Additionally the average magnitude of motion over all organs as shown in Figure 2(b) is of a reasonable value i.e. just above 5 mm.

As in [6], the internal motion was compared with a previous study [12], where organ motion was found via manual segmentation on 20 organs. The motion found from this study is as shown in Figure 3(a).

(a) Mean displacement from a previous study.

(b) Correlation of component displacements.

Figure 3. (a) Mean displacement from a previous study [12]. The labels for the other organs with the exception of the lungs are the same as Fig. 2. (b) Correlation of component displacements.

In Figure 3(a), only the mean value is available as well as a single value for the lungs. The z-axis motion of the lungs is also not available and hence it is assumed to be the average of the z-axis motion of the organs immediately below the diaphragm (liver, stomach and spleen).

The correlation between the results of this previous study and that shown in Figure 2(a) was also found. The correlation was quantified over the proportion of motion over the x-, y- and z-axes. This
A measure of correlation is shown in Figure 3(b) showing a generally high correlation for all organs except the liver (on average 0.8 excluding the liver). This may be attributed to poor delineation due to the low resolution of the images. Note here that the magnitude of motion is not considered as it can differ greatly from person to person.

Lastly as a qualitative assessment, Figure 4(a) shows the motion detected on the anterior surface of the body (at a few selected points arranged in a $5 \times 9$ point grid) while Figure 4(b) shows the trajectory of a few selected points (in any of the orthogonal axes) of the major organs.

Figure 4. 1D trajectory of selected points of (a) the anterior body surface and (b) major organs.

From both Figures 4(a) and (b) it can be seen that the peaks occur at roughly the same time points and hence it can be said generally that there is correlation between the internal and external motion extracted using different methods. However, a more quantitative assessment is described in subsection 3.2.

3.2. Correspondence of Internal and External Motion
As the motion found is high dimensional (45 for external motion whereas internal motion is found over around 500,000 voxels), dimensionality reduction is applied to both internal and external motion separately using principal component analysis (PCA). The number of dimensions was reduced to one less than the number of data points i.e. 34, due to the rank of the data matrices for the internal and external motion respectively. Both types of motion in their respective PCA spaces are as shown in Figures 5(a) and (b).

To show the partial correspondence of internal and external motion, the correlation of the first PC of internal motion with all selected external points was found. This is shown in Figure 6(a) where the correlation is high (magnitude around $\pm 1$) except for a few points due to uncertainty from the low image resolution.

Additionally, the full correspondence was found by calculating the correlation of all PCs of internal motion with all PCs of external motion. This is shown in Figure 6(b) where only the first few respective PCs of internal and external motion show high correlation.

Lastly the first PC of internal motion is plotted against the first PC of external motion as shown in Figure 7. Here the phenomenon of hysteresis [13] is evident and serves as an additional reinforcement that the motion found is reasonable and can represent the true internal and external motion.
Figure 5. Motion of (a) the anterior body surface and (b) major organs in their respective PCA spaces.

Figure 6. Fig. (a) shows the correlation between the surrogates at selected surface points and the first PC of organ motion. Columns and rows refer to the grid of surface points. Fig. (b) shows the correlation between PCs of organ and surrogate motion.

4. Conclusion

The analysis in Section 3 shows that respiratory motion (both of the organs and of the anterior body surface) can be found from 4D MRI despite the low spatial and temporal resolution. This is strengthened by the results that show that the detected motion exhibits features reported in previous measurement. An advantage of the image-based approach allows motion to be extracted over the whole field of view as opposed to motion found from fiducials.

However, there are still avenues for improvement in future work. Firstly the analysis can be extended to all five volunteers in the dataset as well as using larger datasets. Secondly, surface motion can be captured using actual cameras so as to become a totally separate source of measurement from internal motion which is found from dynamic volumetric images. Lastly, a feasible motion compensation approach is to be implemented. While many approaches have been researched, there is still the question of an implementation which is clinically feasible [14].
Figure 7. Joint trajectory for the first respective PCA projection of (internal) organ motion, and (external) surrogate motion.

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References
[1] A reference Keall P J, Mageras G S, Balter J M, Emery R S, Forster K M, Jiang S B, Kapatoes J M, Low D A, Murphy M J, Murray B R, Ramsey C R, van Herk M B, Vedam S S, Wong J W and Yorke E 2006 The management of respiratory motion in radiation oncology report of AAPM Task Group 76 Tech. rep. American Association of Physicists in Medicine
[2] Yang W, Fraass B A, Robert R, Nissen N, Lo S, Jamil L H, Gupta K, Sandler H and Tuli R 2014 Radiation Oncology
[3] Marx M, Ehrhardt J, Werner R and Handels H 2014 Int J CARS \textbf{9} 401 - 409
[4] Boye D, Lomax T and Knopf A 2013 Med Phys \textbf{40}
[5] Miquel M E, Blackall J M, Uribe S, Hawkes D J and Schaeffter T 2014 Physica Medica \textbf{29} 214 - 220
[6] Abd Rahni A A, Lewis E and Wells K 2013 SPIE Medical Imaging: Image Processing vol 8669 p 866930
[7] Abd Rahni A A, Lewis E and Wells K 2013 SPIE Medical Imaging: Image Processing vol 8669 p 86692Z
[8] Tsoumpas C, Buerger C, King A P, Mollet P, Keereman V, Vandenberghhe S, Schulz V, Schleyer P, Schaeffter T and Marsden P K 2011 Phys Med Biol \textbf{56} 6597 - 6613
[9] Abd Rahni A A, Lewis E and Wells K 2013 IEEE ICSIPA pp 232 - 236
[10] Modat M, Ridgway G R, Taylor Z A, Lehmann M, Barnes J, Hawkes D J, Fox N C and Ourselin S 2010 Comput. Methods Programs Biomed. \textbf{98} 278 - 284
[11] Ourselin S, Stefanescu R and Pennec X 2002 MICCAI vol 2489 pp 140 - 147
[12] Segars W P, Mori S, Chen G T Y and Tsui B M W 2007 IEEE NSS/MIC Conf Rec vol 4 pp 2677 - 2679
[13] Escolar J and Escolar A 2004 Histol Histopathol \textbf{19} 159 - 166
[14] McClelland J R, Hawkes D J, Schaeffter T and King A P 2013 Med Imag Anal \textbf{17} 19 - 42