Statistic Model of Respiratory Motion by Using Dynamic MRI

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Introduction

The accurate delivery of medical treatments to internal organs that are subject to considerable respiratory motion has proved to be difficult. A motion model that can predict the internal motion from respiratory surrogate signals (e.g. the displacement of points on the skin surface) can help improve this situation. This abstract present a method for constructing such a model from dynamic MR data using a statistical technique, Canonical Correlation Analysis (CCA) [1], and evaluates and compares the accuracy of the model with a previously reported modelling technique using Principal Component Analysis (PCA) [2, 3].

Method

Given a p-dimensional random variable $\boldsymbol{X}$ and a q-dimensional random variable $\boldsymbol{Y}$ ($q < p$), both of which have zero mean, CCA transforms variables $\boldsymbol{X}$ and $\boldsymbol{Y}$ to a series of linear subspaces (equation 1) so that the projections of $\boldsymbol{X}$ and $\boldsymbol{Y}$ in the linear subspaces have maximum correlation

$$\boldsymbol{X} = w_x^{-1}\boldsymbol{U} \text{ and } \boldsymbol{Y} = w_y^{-1}\boldsymbol{V} \qquad (1)$$

$\boldsymbol{U}$ and $\boldsymbol{V}$ are referred to as canonical variates. By definition, $\boldsymbol{U}$ and $\boldsymbol{V}$ have the maximum possible correlation. Therefore it is possible to use a linear regression to describe $\boldsymbol{U}$ by using $\boldsymbol{V}$ or vice versa (equation 2).

$$\boldsymbol{U} = \boldsymbol{B}\boldsymbol{V} \qquad (2)$$

By combining equation (1) and (2), we have equation (3):

$$\boldsymbol{X} = w_x^{-1}\boldsymbol{B}w_y\boldsymbol{Y} \qquad (3)$$

If the linear relationship between vectors $\boldsymbol{X}$ and $\boldsymbol{Y}$ is known and does not change considerably over time, equation (3) can be considered as a predictive model. In this study, vector $\boldsymbol{X}$ represents the internal organ motion extracted from dynamic MR volumes of the lungs and surrounding anatomy (5x5x5mm, FOV: 480x480x265mm) using a B-Spline based non-rigid registration algorithm. Vector $\boldsymbol{Y}$ represents the skin surface motion extracted from the same MR volumes. By using equation (3), we can predict the internal organ motion from the external skin surface motion.

To evaluate the accuracy of the CCA model, MR data were acquired from four volunteers. For each volunteer, 60 dynamic MR volumes were acquired over 30 seconds, covering 5-7 respiratory cycles. MRI was performed on a 1.5T Philips Achieva MR Scanner in conjunction with a 32-channel coil array (Philips Research, Hamburg). The internal organ motion was represented by the B-spline registration results (15x15x10=2250 control points with 40x40x40mm spacing). 20 skin surface motion signals were used as the respiratory surrogates. To test the accuracy of the models a leave-12-out strategy was used (12 volumes covered at least one respiratory cycle in all subjects). CCA models were built from 48 registrations and used to predict the missing 12. This was repeated until all 60 registrations had been predicted. The predictions were compared with the results of the image registration which was used as the gold standard. In addition, we compared the results from the CCA model with those of a PCA-based model.

Results

Table 1 summarizes the mean absolute error (MAE) of the CCA model and the PCA model. In 3 out of 4 cases, the accuracy of the CCA model is superior to the PCA model in term of MAE. For subject 2, the accuracy of the PCA model is marginally higher than the CCA model. Overall, the performance of the CCA model appears to be more stable. For all the four subjects, the CCA model consistently produces satisfactory results while the accuracy of the PCA model varies. Figure 1 shows the mean respiratory signals (SI direction, subject 1) generated by the image registration in comparison to the CCA and PCA predictions. Figure 2 (a) shows the deformation of the lung during inspiration. Figure 2(b) and 2(c) show the deformation was compensated by using a B-Spline non-rigid image registration algorithm and the CCA model.

Models	Mean absolute error ± standard deviation (mm)			
	Subject 1	Subject 2	Subject 3	Subject 4
PCA	4.84 ± 4.12	2.37 ± 2.31	4.03 ± 4.22	4.21 ± 3.89
CCA	2.86 ± 2.76	2.47 ± 2.53	2.77 ± 2.13	3.11 ± 3.42

Table 1 The accuracy comparison between the PCA model and the CCA model.

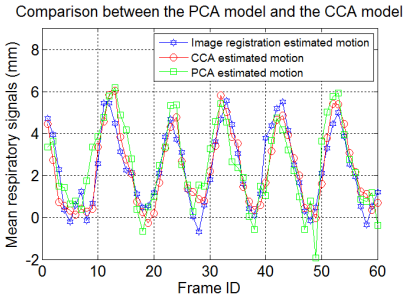
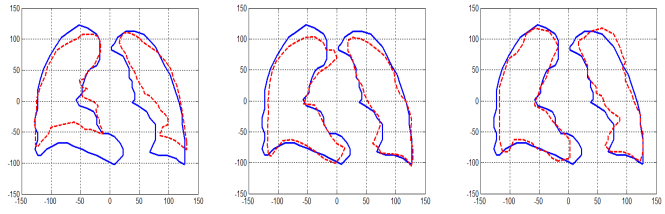


Figure 1. Comparison of the motion signals generated by using an image registration algorithm, the PCA model and the CCA model for subject 1.



(a) (b) (c)

Figure 2. (a) Deformation of the lung at the end inspiration (blue) and the end expiration (red); (b) The end expiration image was aligned to the end inspiration image by using a non-rigid registration algorithm. (c) The end expiration image was aligned to the end inspiration image by using the prediction of the CCA model.

Conclusion

In this abstract we have presented a method of building respiratory motion models using the statistical technique, CCA. We have demonstrated that the CCA models can accurately predict the internal organ motion from respiratory surrogates measured from the skin surface. Additionally, we compared the CCA model with a PCA based modelling technique. The experimental results show the CCA model is superior to the PCA model in 3 out of 4 cases and appears to be more stable than the PCA model. This study demonstrates that CCA can be an accurate and efficient respiratory modelling technique. Future work will evaluate the method using clinical data.

Reference

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