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Two-step subspace mapping based diaphragm displacement prediction by markerless abdominal surface

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INTRODUCTION

To investigate the motion correlation between the internal diaphragm and the external abdominal surface. Then use the surface displacement to predict the diaphragm displacement in real-time.

METHODS

The method includes two stages (as shown in Figure 1): (1) Location measurement based on 3D segmentation; (2) Two-step mapping algorithm. In (1), we perform a threshold segmentation on the 4D CT images to obtain three categories: the lungs, the body, and the background area. Considering the diaphragm being just under the lungs and moving synchronously with the underneath boundary of the lungs, we treat the underneath boundary of lungs as the alternatives of diaphragm. A rectangular region of the abdominal surface are used to represent the abdominal surface, since the area on the two sides of abdominal surface has unstable and irregular movement by experience observer. The mass center is computed to represent the diaphragm and the abdominal surface, and the displacement x and y between two phases for every patient can be further obtained. Since different patients have various organs and the corresponding movement, we perform linear normalization on x and y in the preprocessing step.

The two anatomical organs move differently, which results in the data with different distribution structures. To solve the cross-domain prediction problem, instead of directly performing prediction in original spaces, we first utilize PCA (Principal Component Analysis) to project the two kinds of data into corresponding eigenspaces, which can reduce the data's redundancy and capture its essential characteristics. Then, a subspace mapping is optimized to obtain a linear transformation matrix β as below.

$$\arg\min_{\beta}\left\{\|y - x^T\beta\|_2^2 + \lambda\|\beta\|_2^2\right\} \quad (1)$$

The closed form for Equation (1) can be obtained as below:

$$\beta^{opt} = (x^T x + \lambda I)^{-1} x^T y \quad (2)$$

When new data x_{test} of abdominal surface is input, we can first project them into its eigenspace by PCA and then map them to the diaphragm's corresponding eigenspace using $y_{test} = x_{test}^T \beta^{opt}$. At last, the prediction can be obtained by reverse projection by PCA.

In order to investigate the non-linear correlation between the displacement of the diaphragm and the abdominal surface, TSSM is further extended to kernel TSSM (kTSSM), which optimization function can be written as:

$$\arg\min_{\beta}\left\{\|y - \phi(x)^T\beta\|_2^2 + \lambda\|\beta\|_2^2\right\} \quad (3)$$

where ϕ is a nonlinear mapping function. Using kernel trick, we can directly obtained the prediction in eigenspace as below:

$$y_{test} = K(x_{test}, x)(K(x,x) + \lambda I)^{-1} y \quad (4)$$

where $K(x,y) = \langle\phi(x), \phi(y)\rangle$ is the kernel function and in this study the polynomial kernel and Gaussian kernel are adopted. The simple closed form for the optimization algorithm leads to an extremely fast algorithm, which has potential for improving the accuracy of dose calculation in real-time.

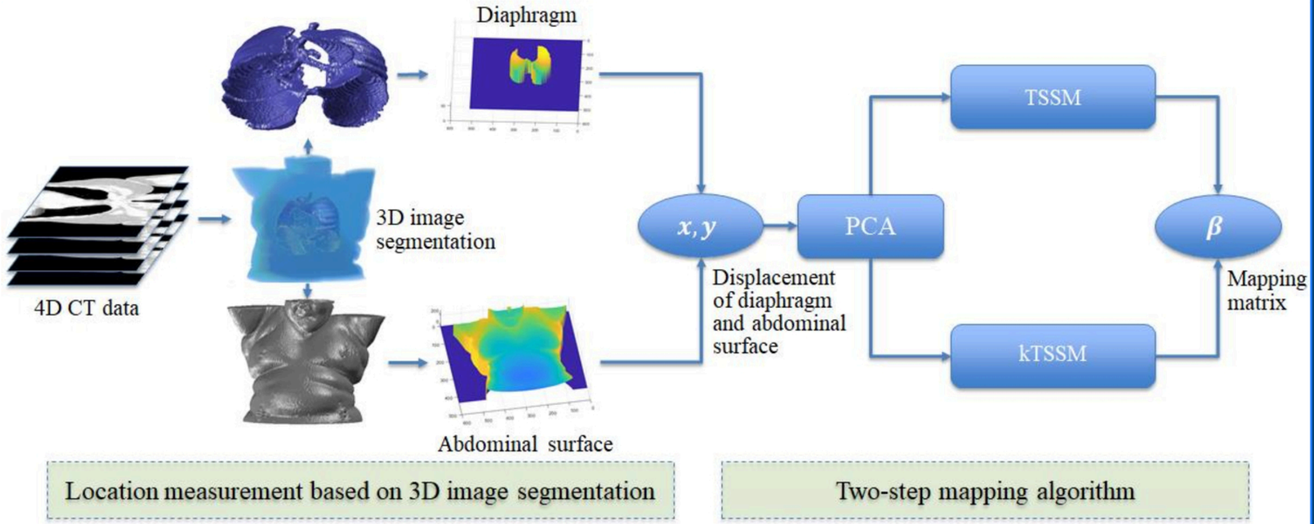

Figure 1: Flowchart of the proposed method, which includes two stages: (1) Location measurement based on 3D segmentation; (2) Two-step mapping algorithm. The first stage employs 3D image segmentation to accurately locate the diaphragm and the abdominal surface. The correlation between the displacement of diaphragm and abdominal surface is investigated in the second stage, which produces the mapping matrix.

DATA AND EXPERIMENT

In this study, we use the clinical datasets acquired with the Philips Brilliance CT Big Bore scanner (Philips Medical Solution, Cleveland, OH). 24 patients are used having each one 10-phase 4D CT series (0,10,⋯,90% of a mean respiratory cycle). No specific indication on how to breathe was given to the patients, but they were asked to breathe normally and regularly.

In experiments, 80% of samples are randomly chosen for model training and the rest samples are for testing. In order to assess the sensitivity of the algorithms, Gaussian noise with $\sigma = \{0.1, 0.2, \cdots, 0.5\}$ are added to both the training data and the testing data. The parameter influence on the algorithm is also analyzed. For the regression optimization, λ is picked up from $\{10^{-10}, 10^{-9}, \cdots, 10^{10}\}$; For Gaussian kernel, σ_{kernel} is equal to the reciprocal of $\{0.1, 0.2, 0.4, 0.6, 0.8, 1.6, 3.2, 6.4, 12.8\}$; For the polynomial kernel $K(x,y) = (wx^T y + c)^d$, $d = \{0.5, 1, \cdots, 11\}$, $c = \{-10, -9, \cdots, 10\}$, and $w = \{-5, -4.5, \cdots, 5\}$, which can guarantee fully investigation of the correlation between the two cross-domain data. For each configuration of parameters, we independently run the algorithm 100 time and obtain the statistic results. Parts of key results are as shown in Table 1. All the experiments are performed at the platform of Inter Xeon 3.6GHz, 32G memory, Windows 10 and Matlab R2019b.

RESULTS

	Without noise			With noise ($\sigma = 0.5$)		
	MSE	R^2	MAPE	MSE	R^2	MAPE
linear model [1]	0.10	0.90	25.93	0.25	0.83	74.09
	(0.46)	(0.48)	(75.60)	(0.23)	(0.14)	(1.09e+03)
TSSM (linear)	0.06	0.93	23.68	0.22	0.87	56.60
	(0.02)	**(0.02)**	**(22.43)**	(0.10)	(0.05)	(1.86e+03)
kTSSM (polynomial)	**0.05**	**0.93**	26.76	**0.14**	**0.90**	55.50
	(0.02)	**(0.02)**	(22.47)	**(0.07)**	**(0.04)**	(490.47)
kTSSM (Gaussian)	0.08	0.92	**19.60**	0.20	0.87	**52.22**
	(0.02)	(0.02)	(23.87)	(0.08)	(0.04)	**(307.15)**

Table 1: Experiment results. For each metric of one algorithm, the upper value is the best result the algorithm can obtain and the lower value in brackets is the standard deviation of 100 independent runnings corresponding to the parameter configuration of the best result. For MSE and MAPE, we record the minimum value, and for R2, we record the maximum value. For each column of the metric, the best result of the four algorithm is emphasized with bold.

In Table 1, four algorithms are compared, which are the linear model in Reference [1], TSSM of linear model, and kTSSM with polynomial kernel and Gaussian kernel. For each algorithm, we choose the best result of the metrics and compute the standard deviation of 100 independent runnings corresponding to the parameter configuration of the best result. It can be noticed from Table 1 that the proposed algorithm outperform the state-of-the-art linear model [1]. For the data without noise, kTSSM can reach the best result especially for kTSSM with polynomial kernel, but TSSM can also perform quite well and more stable than others. For the data with noise, the performance of the non-linear kTSSM is much better than those of the linear models. Based on the observation above, we can conclude the kTSSM with polynomial kernel can obtain the best performance for the displacement prediction of diaphragm according to the displacement of abdominal surface, but the TSSM of linear model is quite stable and enough to make such prediction especially for the data without noise.

REFERENCES

[1] K. T. Malinowski, et al, "Mitigating errors in external respiratory surrogate-based models of tumor position," *International Journal of Radiation Oncology* Biology* Physics*, vol. 82, no. 5, pp. e709-e716, 2012

CONCLUSIONS

The markerless method based on 3D image segmentation can accurately locate the diaphragm and the abdominal surface. The kTSSM with polynomial kernel can obtain the best prediction performance, but the TSSM of linear model is stable to make prediction, especially for the data without noise.

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