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Original Article

A Simulation Study on Patient Setup Errors in External Beam Radiotherapy Using an Anthropomorphic 4D Phantom

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Abstract

Introduction
Patient set-up optimization is required in radiotherapy to fill the accuracy gap between personalized treatment planning and uncertainties in the irradiation set-up. In this study, we aimed to develop a new method based on neural network to estimate patient geometrical setup using 4-dimensional (4D) XCAT anthropomorphic phantom.

Materials and Methods
To access 4D modeling of motion of dynamic organs, a phantom employs non-uniform rational B-splines (NURBS)-based Cardiac-Torso method with spline-based model to generate 4D computed tomography (CT) images. First, to generate all the possible roto-translation positions, the 4D CT images were imported to Medical Image Data Examiner (AMIDE). Then, for automatic, real time verification of geometrical setup, an artificial neural network (ANN) was proposed to estimate patient displacement, using training sets. Moreover, three external motion markers were synchronized with a patient couch position as reference points. In addition, the technique was validated through simulated activities by using reference 4D CT data acquired from five patients.

Results
The results indicated that patient geometrical set-up is highly depended on the comprehensiveness of training set. By using ANN model, the average patient setup error in XCAT phantom was reduced from 17.26 mm to 0.50 mm. In addition, in the five real patients, these average errors were decreased from 18.26 mm to 1.48 mm various breathing phases ranging from inhalation to exhalation were taken into account for patient setup. Uncertainty error assessment and different setup errors were obtained from each respiration phase.

Conclusion
This study proposed a new method for alignment of patient setup error using ANN model. Additionally, our correlation model (ANN) could estimate true patient position with less error.

Keywords: Artificial neural network, Patient setup, Correlation model, External radiotherapy

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1. Introduction

In external beam radiotherapy, when treatment planning is implemented individually, the patient should be immobilized in front of the beam during treatment to localize target at each treatment session [1, 2]. However, several uncertainties in the patient geometrical setup may cause undesirable effects on the prescribed 3-dimensional (3D) uniform dose that must be delivered into tumor volume.

The results showed some over- and/or under-dosage in tumor and healthy surrounding organs. These uncertainties known as inter- and intra-fractional error are divided into two groups of random and systematic errors. Inter-fractional motion error consists of patient body misalignments during each irradiation session or patient body displacements between different daily fractions. On the other hand, intra-fractional motion error causes organ motion and deformation between different fractions over a course of treatment. This uncertainty may occur alone or in combination, yielding poor targeting accuracy [3-5].

Therefore, patient-positioning setup is a challenging issue in the quality of dose delivery to tumor volume and healthy tissue in external radiotherapy. To this end, patient positioning verification at each irradiation fraction and/or between different fractions is of great importance to align 3D tumor volume against irradiation beam during treatment [6].

Several factors are at play in conventional patient positioning setup, performed by several methods, including immobilization system and/or experience of operators to immobilize target localization irradiation in front of beam at each treatment session [1]. In addition, application of body detection systems (optoelectronic or laser spot scanning) in combination with indication markers for calculating misalignment between patient position and reference point are of major significance [7-10].

Recently, a novel method based on registration and artificial neural network (ANN) was proposed to align patient geometrical setup in breast radiotherapy. In this method, treatment parameters were calculated using registration method, and then were applied to the ANN model. Afterwards, training set was gathered from laser spot, and ANN was used to fill the gap between individual treatment and uncertainty even at each treatment session [9-12]. Some of these methods, which are commercially available, are applied under clinical conditions [8, 13, 14].

Former studies examined the applied body detection systems (optoelectronic or laser spot scanning) with combination of indication markers to align patient setup. In this study, for verification of geometrical setup, all the possible positions of patient couch with three external markers (placed on the chest of XCAT phantom) were simulated based on XCAT phantom. Finally, we assembled two large symmetric and asymmetric datasets (in Methods and Materials section they are thoroughly explained).

Comprehensive studies were performed taking into account different aspects of the available correlation models in our previous reports [14-16]. Through training ANN by these datasets, model configuration was created. After that configuration model, ANN model was used to align un-couched patient position. Large amounts of patient displacement, collated as the symmetric and asymmetric databases, were used as a training set for model construction. Among the produced databases by XCAT, asymmetric dataset illustrates real patient displacements. In addition, there are some differences between conventional patient positioning (opto-electronic or laser spot scanning) and our model. In the conventional method with combination of fiducial markers, which is turned out to be inadequate for filling up the accuracy gap between personalized treatment plan and the uncertainties in the irradiation set-up. They provide an acceptable trade-off between swiftness and patient positioning accuracy, but their efficacy is totally committed to operator's attention, as they lack any quantitative on-line control on the quality of the specific repositioning and patient actual immobility during the irradiation.

But in this study, location of patient switch by external markers and ANN model is used for real-time verification of patient geometric set-up instead of using (opto-electronic or laser spot scanning). Moreover, the ANN model was used to setup realignment and continuous tracking. In addition, the technique was validated through simulated activities by using reference 4D CT data acquired from five subjects.

ANN is a computational tool, which is based on the properties of biological neural systems. Neural network, as a robust non-linear method, can numerically realize the complex relationships through imperfect or missing information, where output of conventional mathematical approaches contains large degrees of error [17-19].

In the pre-treatment step, the model was trained based on the experimental data in order to determine model structure parameters. Our model was configured using training set at the pre-treatment step. Training set in this step includes external marker motions versus corresponding reference points. After model configuration, correlation model can estimate misalignment as model output that is required for corrective patient positioning. When the proposed ANN model is established using training set, ANN model is able to determine patient alignment against beam trajectory by minimizing inter-fractional motion uncertainties.

It should be considered that ANN performance highly depends on the number of training data points gathered at pre-treatment step. Increasing the number of data pairs (three external markers versus patient position couch), training step may lead to improved model construction. In this study, an explicit investigation was performed on the process of training sets for optimal data selection in the configuration of our ANN model. Then, using only external markers as model input, patient displacement is determined as model output, and the required correctives are implemented by means of patient couch movement.

Two data categories were generated as symmetric and asymmetric databases for model training at one breathing cycle through 4D XCAT [20] anthropomorphic phantom, developed by W.P. Segars. This phantom, which is commercially available, works based on Spline method and includes 3D human anatomy information plus breathing and heartbeat motions versus time as the fourth dimension [21].

Additionally, along with 4D XCAT phantom, A Medical Image Data Examiner (AMIDE) [22] software (v. 1.15) is utilized to generate information regarding 1) surface body motion by means of external markers located at the chest and 2) motion extraction of patient couch, pre-defined as a reference point. Comprehensive studies were conducted considering different aspects of the available dataset and prediction model in our previous reports [14-16]. In addition, the technique was validated through simulated activities by using reference 4D CT data acquired from five patients.

Results were expressed by computing the root mean square error (RMSE) between the desired output (benchmarked patient position) and network predicted outputs (obtained by applying the training datasets on ANN model). Final analyzed results represent that the ANN model is a powerful tool to fill the accuracy gap between personalized treatment planning and uncertainties in the irradiation setup, which our ANN could reasonably estimate true patient position and possible displacement with less errors.

Furthermore, ANN performance accuracy is different for each patient on a case-by-case basis. Moreover, patient geometrical setup is depended on the comprehensiveness of training set required for model construction. A reasonable training set must include all the possible rotation and translation displacements that may happen to patient at the initial incorrect setup. Different breathing phases ranging from inhalation to exhalation were taken into account for patient setup. Uncertainty error was assessed using ANN and different set-up errors were obtained in each different respiration phase.

2. Materials and Methods

A simulation study was performed using anthropomorphic phantom that can model shapes and structures of complex organs in human body along with motion of dynamic organs such as respiratory system and heartbeat motions [23]. The available phantoms are divided into two major categories as 1) pixel-based and 2) geometric-based phantoms.

A pixel-based phantom usually depends on patient data that are limited to a particular predefined anatomy [24]. In contrast, a geometry-based phantom is used for anatomical variations taking into account multiple resolutions [25]. Moreover, another phantom known as XCAT phantom, which is a combination of pixel-based and geometry-based phantoms, was developed including motions at the thorax region of patient body [21]. This XCAT phantom uses non-uniform rational B-splines-based (NURBS-based) Cardiac-Torso methods with spline-based anthropomorphic model for creating the Visible Human dataset including a) 4D modeling of breathing and b) heartbeat [21].

The organ motions caused by respiration and heartbeat were incorporated into the 4D XCAT phantom. In this study, five different respiratory cycles were generated with reasonable breathing amplitude and frequency to mimic real respiratory pattern.

We used XCAT phantom and AMIDE to assess displacements caused during patient geometrical setup. AMIDE was applied to process visual 4D CT data [22]. Firstly, a set of 4D CT data were generated using XCAT phantom in a predefined respiratory cycle with a reasonable breathing amplitude and frequency to mimic real respiratory pattern (Figure 1).

The generated 4D CT data were then imported to AMIDE [22], and by adding external fiducial marker mode, the three points were uniformly distributed onto the surface of phantom. It should be considered that the external markers can be located at every point onto the chest and abdominal regions of patient body surface. The scheme of the depicted points started from abdominal region with an average of 5 cm distance in horizontal direction. Figure 2 shows typical external markers placed on the patient's (No. 2) skin.

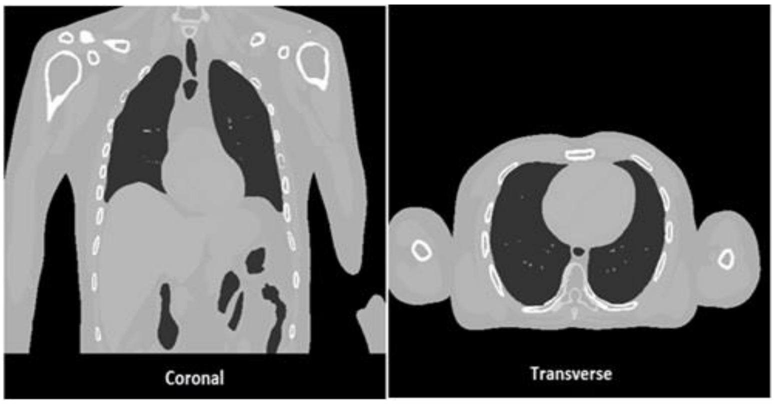


Figure 1. Two typical computed tomography images of the thorax region generated by 4-dimensional XCAT phantom

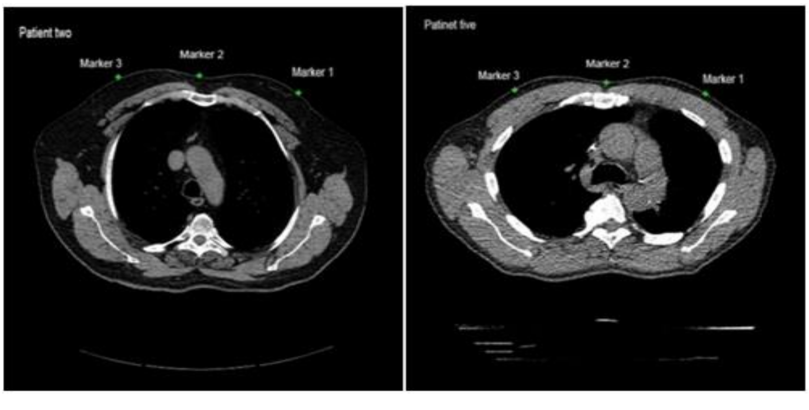


Figure 2. The location of external markers (green dots) onto chest region of body surface

To investigate patient displacements, all the possible roto-translation variations that might happen during patient setup were simulated by AMIDE. Table 1 illustrates the displacement range of patient positioning in both rotation and translation modes. It should be noted that all patient mismatches in symmetric and asymmetric conditions were simulated with 7360 separate data points using position information from three external markers at each data point.

In the symmetric dataset, rotation and torsion parameters have similar behaviors; for example, if rotation is considered 3 degrees, torsion parameter should be considered 3 degrees, as well. On the other hand, in asymmetric dataset, rotation and torsion parameters are actual behaviors (not same behaviors), that is, when rotation parameter is assumed 3 degrees, torsion parameter can range between -9 and 9 degrees. For translation parameters (x, y, z), each of the parameters has actual behavior.

Table 1. Possible patient displacements as rotation and translation

Rotation (degree)	Torsion (degree)	Translation (mm)
0	0	0
±3	±3	±15
±6	±6	±30
±9	±9	±45

Under asymmetric conditions, a parameter of rotation or translation was considered to be fixed and other residual parameters differed in the range given in Table 1. The gathered data can be optimal for simulating patient setup at the pretreatment step of radiation treatment. In this study, we used the data from external markers motion in correlation with a reference point, pre-defined as a patient couch position. To this end, external-reference configuration motion data was synchronously captured, a correlation model was configured before treatment using this synchronized data known as “training set”.

After configuration, the correlation model can perform automatic, real time verification of geometrical setup. Moreover, the non-deterministic modeling performed by ANN minimizes sensitivity to intra- and inter-fractional, non-rigid movement of patient body. This model is fed by motion information of external markers. It is worth mentioning that the predictive model accuracy is highly dependent on the quality and even quantity of database required for model configuration during the learning process.

Moreover, the generated motion data integrated from XCAT phantom were proposed to be extended to real patient data. For this purpose, a fixed point was assumed at near middle loin (T6), and CT data from real patients were set on the fixed point. The fixed point was used for fixing the geometries phantom and the geometry of real patients. After fixing the geometries, distances between external markers placed on the surface of patients were calculated with external markers implemented on the surface of the phantom.

The distances in each patient included the three parameters of x, y, z and are used to extend dataset from phantom to patients; in so doing, two parameters were defined, including 1) distance between location of external marker on the phantom and patient and 2) rotation coefficient in location external markers on patient surface. Figure 3 shows the necessary distances calculated for extension of data from phantom to patient. Then, two correction factors were implemented for extension of roto-translation data from phantom to CT data of real patient by means of MATLAB code. Figure 3 demonstrates a typical flowchart extension from XCAT phantom to a patient. Comprehensive studies were conducted taking into account different aspects of available correlation models in our previous reports [14-16].

Table 2. Patients’ computed tomography data

Patient	Image dimension	Pixel dimension (mm)
Patient one (phantom)	512×512×381	0.5×0.5×0.5
Patient two	512×512×141	0.97×0.97×2
Patient three	512×512×169	0.97×0.97×2
Patient four	512×512×170	0.87×0.87×2
Patient five	512×512×187	0.78×0.78×2
Patient six	512×512×161	1.17×1.17×2

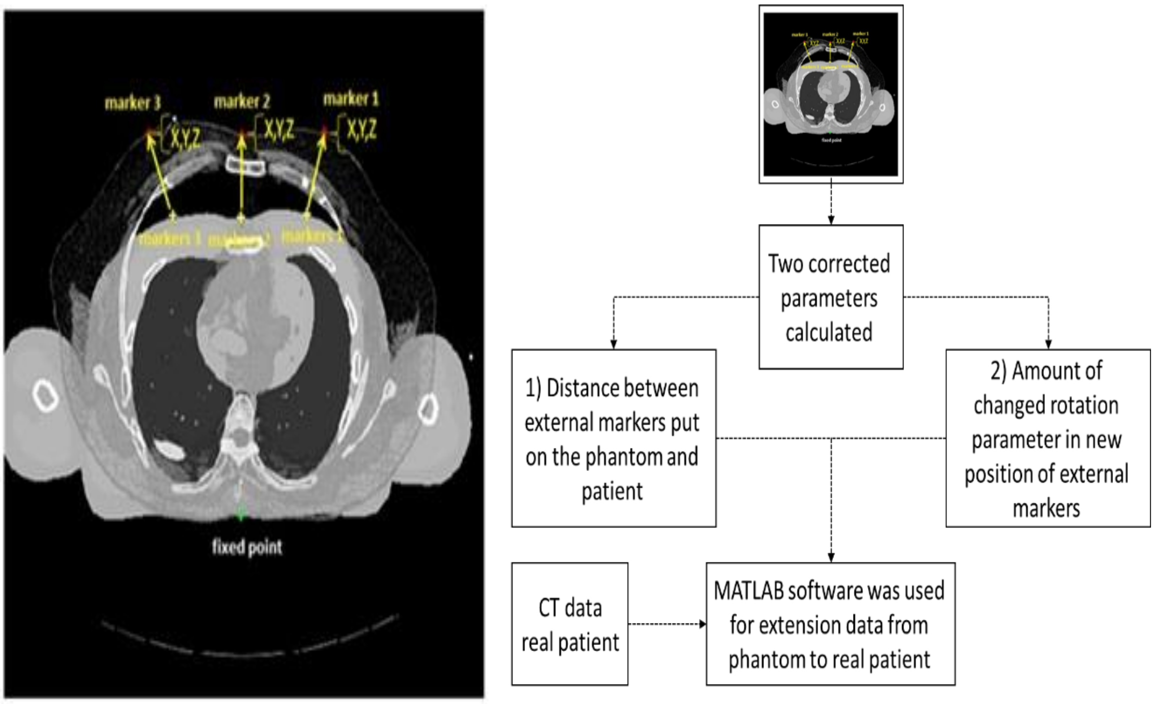


Figure 3. A typical flowchart extension from XCAT phantom to a patient. For extension of external motion data from phantom surface (yellow dots as markers) to surface body of real patient (red dots as markers) two corrected parameters must be calculated. Moreover, for fixed geometry of phantom and patient a green dot represents a fixed point**.**

The 4D CT data of five real patients used in this work are presented in Table 2.

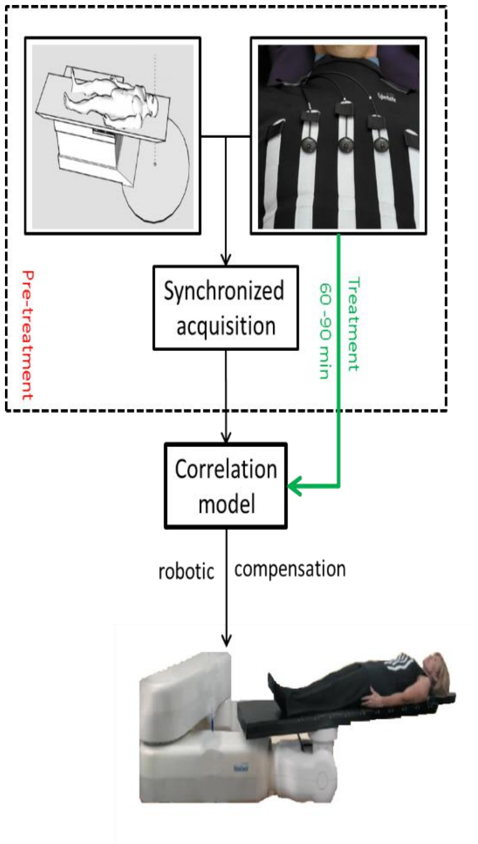
The applied non-deterministic correlation model in this work was based on the ANN [25-30]. This model was selected to correlate synchronized external motion data with a predefined reference point, due to its superior performance compared to conventional mathematical approaches. Conceptually, ANNs are highly effective in finding out the complex relationship between imperfect database and high variability, where mathematical methods are impossible or difficult to solve [31].

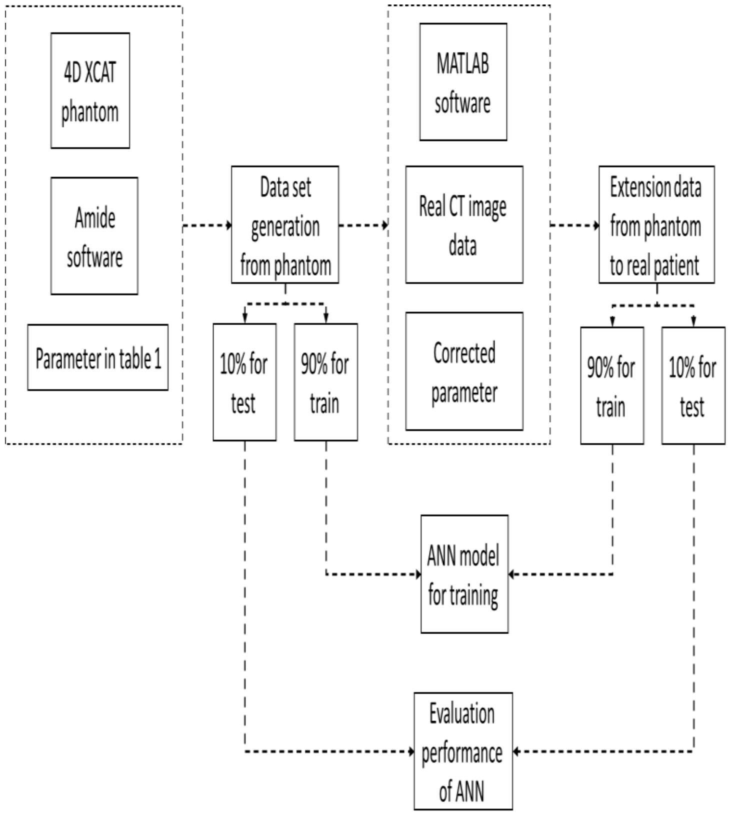
ANN model should be configured using training set before its performance at patient setup. Training set in this step includes external marker motions versus corresponding reference point position, that is, patient couch position. In this step, the parameters of ANN structure are determined by means of training set. Therefore, the number of training set and its quality is significantly effective in model performance for better patient setup. We developed our ANN correlation model by implementing MATLAB toolbox (The Math Works Inc., Natick, MA).

ANN is presented as a powerful tool in modeling numerous processes using numeric power of neural network system. In this study, we used the strengths of ANN, particularly as a correlation model for verification of geometrical setup, where same calculations with normal mathematical methods are difficult or less accurate. When the model is configured, it is able to estimate patient displacement only using external marker data.

Figure 4-a-left shows ANN model training and performance for patient geometrical setup.

In Figure 4-b-right, workflow of performance of this investigation and the link between these tools is demonstrated. Our ANN correlation model must be trained using dataset in synchronized form in training step. After configuration, the model is able to re-align patient position as a function of time only using the selected external motion data.





(a) (b)

Figure 4- a) Artificial neural network model configuration and performance using external markers correlated with patient couch position. b) Workflow of performance of this investigation and link among the tools

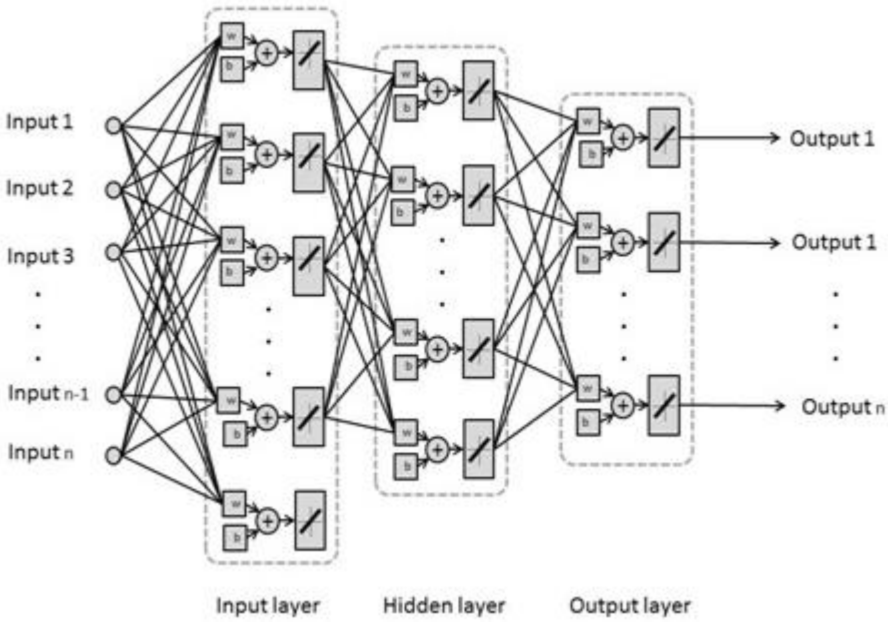


Figure 5. The structure of artificial neural network (ANN) was proposed for the automatic, real time verification of geometrical setup. In addition, the ANN model includes 27 input layers, three hidden layers, the first layer of which has six neurons, the second layer contains seven neurons, and the third layer has four neurons and four output layers

The ANN employed in this work includes three-layer perceptron, the first layer of which has six neurons, the second layer consists of seven neurons, and the third layer comprises of four neurons. Transfer function and number of neurons are determined based on trial and error method. During training step, ANN uses the Levenberg-Marquardt learning algorithm. Figure 5 shows the structure of the neural network perceptron.

In pre-treatment, 90% of all the dataset was used for train ANN model and 10% of the dataset was employed for evaluation of ANN model performance. After the model configuration is determined for different positions, ANN model can immediately verify patient geometric setup and implement the required modifications for patient setup. All the information regarding the ANN model are presented in table3.

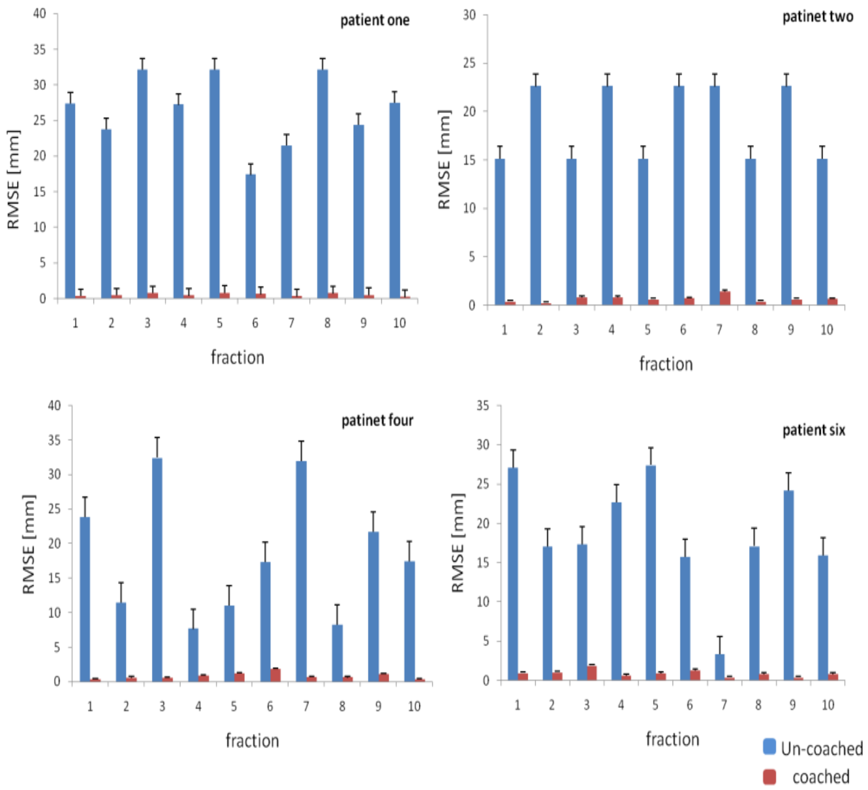


Figure 6. Root-mean-squared errors of artificial neural network correlation model at phantom and three patients in comparison with un-couched (patient misaligned) and couched (output model).

Table 3. The structure of the artificial neural network (ANN) model.

Type/count	Feature
Feed-forward back propagation	Type of network
3	Number of layers
6	Number of neurons in layer 1
7	Number of neurons in layer 2
4	Number of neurons in layer 3
27	Number of inputs
4	Number of outputs
Pure line	Transfer function of the first layer
Pure line	Transfer Function of the second layer
Pure line	Transfer function of third layer
Gradient descent	Back propagation network training function
Gradient descent	Back propagation weight/bias learning function

3. Results

To evaluate performance of models, the results are expressed by computing the root mean square error (RMSE) between benchmarked, and model output was calculated according to the following metric:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2} \quad (1)$$

Where, N is the number of predicted samples, $\boldsymbol{A_i}$ is the $\boldsymbol{i_{th}}$ actual output in the dataset, and $\boldsymbol{P_i}$ is the $\boldsymbol{i_{th}}$ predicted output by the model.

In external-beam radiotherapy, use of external markers is one of the most reliable tools for patient setup. The main challenging issue in this approach is the accuracy of patient position, which heavily depends on correlation model and location of external markers that are the objectives of this study. Figure 6 shows RMSE calculated between ANN estimated output and real given position at ten fractions of radiotherapy course in comparison with un-couched condition, where no patient alignment is happening with operator. The results are shown for phantom and three real patients from our patient group.

In fact, the calculated RMSEs represent the uncertainty error of the ANN model at alignment of four cases. Table 4 depicts the average of RMSEs between model output and ground truth data in phantom of our patient group over the course of radiation treatment of each case.

Table 4. Average root-mean-squared errors of un-couched and artificial neural network model over phantom and patient group

Patients	Average RMSE un-couched (mm)	Average root-mean-squared errors of artificial neural network output (couched) (mm)
Patient # one (phantom)	17.26	0.5047
Patient # two	18.57	1.4616
Patient # three	19.54	0.8538
Patient # four	20.01	1.476
Patient # five	19.14	2.7284
Patient # six	16.18	0.8708

Table 5. The effects of roto-translation parameters on model performance

Patients	Root-mean-squared errors (RMSE) (mm) rotation	RMSE (mm) torsion	RMSE (mm) RL direction	RMSE (mm) AP direction
Patient # one (phantom)	0.307	0.2616	0.6909	2.3946
Patient # two	0.0874	1.4028	0.7122	0.8319
Patient # three	0.1009	1.3653	0.6777	2.422
Patient # four	0.1509	1.1296	0.8337	3.3619
Patient # five	0.1069	1.3631	0.8592	3.3403
Patient # six	0.1286	1.3304	0.7753	2.5296

RL: right lateral direction, AP: Anterior-Posterior

Based on investigations on the 4D XCTA phantom, the motion dataset in Left-Right (LR) direction is highly limited, and this dimension could be eliminated from total database and the remaining motion data include both anterior-posterior (AP) and superior-inferior (SI) directions.

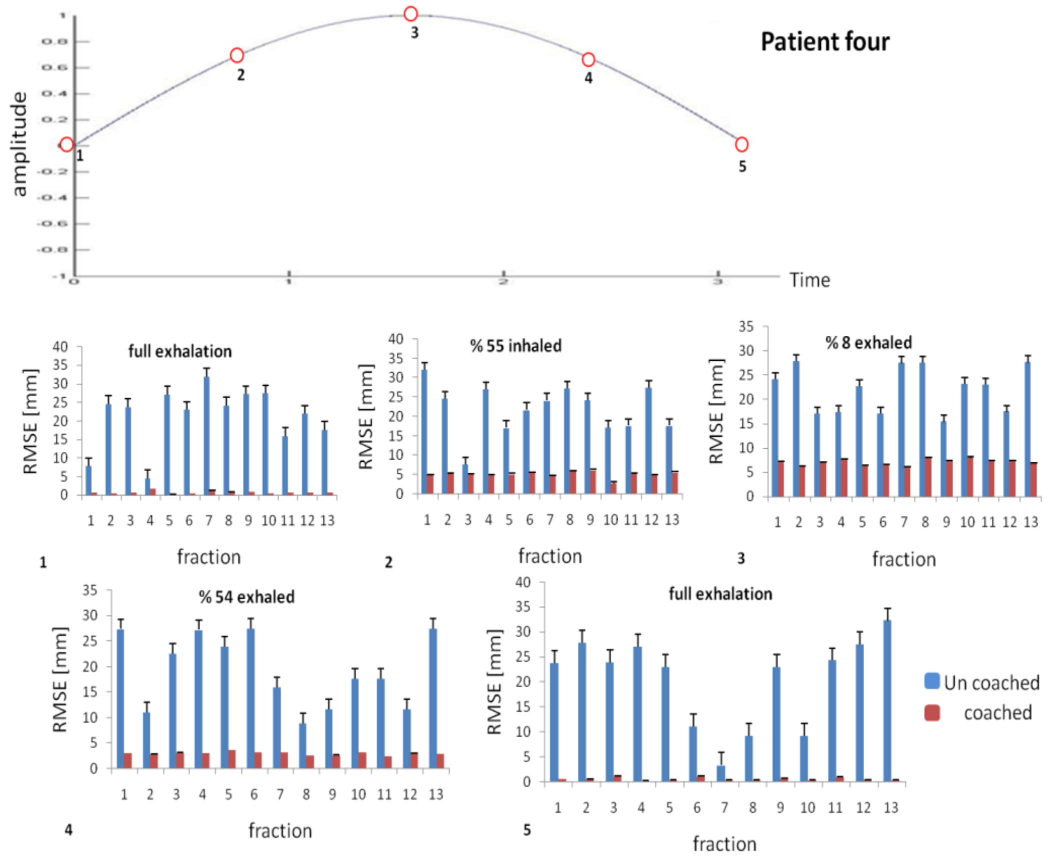


Figure 7. The effects of different breathing phases on model performance; each plot is associated with a breathing phase

As a result of ANN model, the most effective parameter in patient alignment is changing it at AP direction. When the ANN model is configured with the training data, it is only fed by external marker data captured at a moment of the respiratory cycle by means of external monitoring system. Therefore, the position of external markers that are randomly distributed among respiratory cycles may be effective in model performance. For testing this issue, model performance accuracy in patient displacement was considered at five breathing phases of one typical patient and the results are shown in Figure 7.

As can be noted in Figure 7, data captured at the exhalation phase of breathing can provide the best input dataset for optimum patient displacement due to maximum relaxation of patient's organs in this phase.

4. Discussion

In external beam radiotherapy, when treatment planning is individually implemented, the patient should be immobilized during treatment in front of the beam in order to localize target at each treatment session. For this purpose, patient positioning verification at each irradiation fraction and/or between different fractions may be significantly important to align 3D tumor volume against irradiation beam during treatment.

In this study, patient geometrical setup was comprehensively simulated using 4D XCAT anthropomorphic phantom. This phantom uses NURBS-based Cardiac-Torso method with spline-based model to access 4D modeling of breathing and heartbeat motions. Moreover, AMIDE was utilized to capture surface body motion information by means of external markers located at the chest and motion

extraction of patient couch, pre-defined as a reference point.
All the possible roto-translation displacements that might happen at initial patient position before alignment by operator were taken into account. The patient displacements were proposed to vary in a range from -9 to 9 degrees rotation and -45 to 45 mm in translation, and the gathered data were saved as symmetric and asymmetric log files. In addition, for further investigation, the captured data by phantom was extended to five real patients to avoid the simplicity of phantom during calculations.
Patient geometrical setup must be performed at each fraction during a course of radiation treatment by determining patient displacement. In some strategies of patient positioning, consistent correlation models are utilized to estimate patient displacement by means of monitoring body surface motion paired with spatial motion of a reference point as a function of time. In this study, a non-deterministic correlation model based on ANN was proposed to estimate patient displacement by using our collected database including external surface body motion synchronized with a patient couch position as a reference point.
In fact, ANN model was proposed to assess the process of our simulation procedure in patient geometrical setup. The ANN, which is a commercially available method, can help with finding out the complex relationship among highly variable databases rather than other conventional mathematical methods, which include immobilization system, experience of operators, and safety margins of the surrounding healthy tissues. It should be considered that the correlation model is only a part of the patient setup process. When patient displacement was predicted by our ANN, corrective process happens by patient couch movement to align tumor volume against therapeutic irradiation beam.
In the per-treatment step, the model was trained based on the experimental data set in order to determine model structure parameters. The ANN correlation model must be learnt and configured using training database. After configuration, the model is ready to estimate patient displacement with an uncertainty error using only external markers position captured in a moment at any arbitrary phase of breathing. Training database in our case study includes 1) external markers motion located at chest representing body surface motion and 2) patient treatment couch position. The paired database was synchronized before using at training step.
As presented in Figure 5, our ANN model can effectively detect patient displacement at 10 fractions in comparison with un-couched position where no alignment happened with operator. Using ANN, the amount of RMSE between model output and real position was significantly reduced compared to un-couched condition.
Patient setup depends on rotation (roll, pitch, and tilt) and translation (shift on x and y directions) parameters, each of which has a unique effect on patient alignment. In this study, the role of each parameter was taken into account. As exhibited in Table 5, AP direction has been the most effective parameter in patient geometry setup.
Since external markers motion data required as input for patient's displacement estimation may be captured at any desired time during respiratory cycle, the amount of this data may affected the ANN model performance. To assess this issue, external markers data were captured at five breathing phases between exhalation-inhalation peaks, and patient setup was conducted separately using ANN model. Results showed that the best patient alignment happened at the exhalation phase, where all organs are almost fixed with least motions.
One concerning issue in this work was configuring an optimum ANN model with less uncertainty error in displacement prediction. Model configuration highly depends on the quality and quantity of training datasets as illustrated before. Both of these features were considered and the results are shown in Figure 5 and Table 4, representing that optimum

performance is achieved when training dataset is perfect. For instance, average error reduction for all the patients was decreased from 18.26 mm to 1.48 mm.

5. Conclusion

A comprehensive simulation study was performed on patient setup using XCAT phantom in combination with AMIDE software using 4D CT data of five real patients. A non-deterministic ANN correlation model was proposed to estimate patient displacement using our database obtained by phantom. Final analyzed results represent that ANN model is able to correctly align tumor volume against irradiation beam with less uncertainty error. Furthermore, the effect of different parameters on model performance in error reduction ranged from training data preparation for model construction to the type and number of model input for patient misalignment estimation. Further studies should be conducted on assessing abilities of ANN model in combination with image registration techniques for patient setup improvement.

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References

1. Verhey LJ Immobilizing and positioning patients for radiotherapy. In: Seminars in Radiation Oncology, 1995. Elsevier, pp 100-114
2. Nankali S, Torshabi AE, Miandoab PS (2015) A Feasibility Study on Ribs as Anatomical Landmarks for Motion Tracking of Lung and Liver Tumors at External Beam Radiotherapy. Technology in cancer research & treatment:1533034615595737
3. Weiss E, Vorwerk H, Richter S, Hess CF (2003) Interfractional and intrafractional accuracy during radiotherapy of gynecologic carcinomas: A comprehensive evaluation using the ExacTrac system. International Journal of Radiation Oncology* Biology* Physics 56 (1):69-79
4. Britton KR, Takai Y, Mitsuya M, Nemoto K, Ogawa Y, Yamada S (2005) Evaluation of inter-and intrafraction organ motion during intensity modulated radiation therapy (IMRT) for localized prostate cancer measured by a newly developed on-board image-guided system. Radiation medicine 23 (1):14-24
5. Torshabi AE, Riboldi M, Fooladi AAI, Mosalla SMM, Baroni G (2013) An adaptive fuzzy prediction model for real time tumor tracking in radiotherapy via external surrogates. Journal of Applied Clinical Medical Physics 14 (1)
6. Torshabi A, Pella A, Riboldi M, Baroni G (2010) Targeting accuracy in real-time tumor tracking via external surrogates: a comparative study. Technology in cancer research & treatment 9 (6):551-561
7. Spadea MF, Baroni G, Riboldi M, Tagaste B, Garibaldi C, Orecchia R, Pedotti A (2006) Patient set-up verification by infrared optical localization and body surface sensing in breast radiation therapy. Radiotherapy and oncology 79 (2):170-178
8. Baroni G, Ferrigno G, Orecchia R, Pedotti A (2000) Real‐ time opto‐ electronic verification of patient position in breast cancer radiotherapy. Computer Aided Surgery 5 (4):296-306
9. Frosio I, Spadea M, De Momi E, Riboldi M, Baroni G, Ferrigno G, Orecchia R, Pedotti A (2006) A neural network based method for optical patient set-up registration in breast radiotherapy. Annals of biomedical engineering 34 (4):677-686
10. Baroni G, Troia A, Riboldi M, Orecchia R, Ferrigno G, Pedotti A (2003) Evaluation of methods for opto-electronic body surface sensing applied to patient position control in breast radiation therapy. Medical and Biological Engineering and Computing 41 (6):679-688
11. Riboldi M, Gierga DP, Chen GT, Baroni G (2009) Accuracy in breast shape alignment with 3D surface fitting algorithms. Medical physics 36:1193
12. Riboldi M, Baroni G, Orecchia R, Pedotti A (2004) Enhanced surface registration techniques for patient positioning control in breast cancer radiotherapy. Technology in cancer research & treatment 3 (1):51

13. Soete G, Van de Steene J, Verellen D, Vinh-Hung V, Van den Berge D, Michielsen D, Keuppens F, De Roover P, Storme G (2002) Initial clinical experience with infrared-reflecting skin markers in the positioning of patients treated by conformal radiotherapy for prostate cancer. International Journal of Radiation Oncology* Biology* Physics 52 (3):694-698
14. Miandoab PS, Torshabi AE, Nankali S, Rezai M (2015) The Robustness of Various Intelligent Models in Patient Positioning at External Beam Radiotherapy. Frontiers in Biomedical Technologies 2 (1):347-357
15. Nankali S, Torshabi AE, Miandoab PS, Baghizadeh A (2015) Investigation on Performance Accuracy of Different Surrogates in Real Time Tumor Tracking at External Beam Radiotherapy. Frontiers in Biomedical Technologies 2 (2):381-387
16. Miandoab PS, Torshabi AE, Nankali S (2015) 2D and 3D Optical Flow Based Interpolation of the 4DCT Image Sequences in the External Beam Radiotherapy. Frontiers in Biomedical Technologies 2 (2):404-413
17. Jang J-S (1993) ANFIS: adaptive-network-based fuzzy inference system. Systems, Man and Cybernetics, IEEE Transactions on 23 (3):665-685
18. Riboldi M, Sharp G, Baroni G, Chen G (2009) Four-dimensional targeting error analysis in image-guided radiotherapy. Physics in medicine and biology 54 (19):5995
19. Abraham A (2001) Neuro fuzzy systems: State-of-the-art modeling techniques. In: Connectionist models of neurons, learning processes, and artificial intelligence. Springer, pp 269-276
20. Segars W, Sturgeon G, Mendonca S, Grimes J, Tsui B (2010) 4D XCAT phantom for multimodality imaging research. Medical physics 37:4902
21. Segars WP, Tsui B, Lalush D, Frey E, King M, Manocha D (2001) Development and application of the new dynamic Nurbs-based Cardiac-Torso (NCAT) phantom.
22. Loening AM, Gambhir SS (2003) AMIDE: a free software tool for multimodality medical image analysis. Molecular imaging 2 (3)
23. Zubal IG, Harrell CR, Smith EO, Rattner Z, Gindi G, Hoffer PB (1994) Computerized three-dimensional segmented human anatomy. MEDICAL PHYSICS-LANCASTER PA- 21:299-299
24. Tsui BM, Terry JA, Gullberg GT (1993) Evaluation of cardiac cone-beam single photon emission computed tomography using observer performance experiments and receiver operating characteristic analysis. Investigative radiology 28 (12):1101-1112
25. Gierga DP, Brewer J, Sharp GC, Betke M, Willett CG, Chen GT (2005) The correlation between internal and external markers for abdominal tumors: implications for respiratory gating. International Journal of Radiation Oncology* Biology* Physics 61 (5):1551-1558
26. Yan H, Yin F-F, Zhu G-P, Ajlouni M, Kim JH (2006) The correlation evaluation of a tumor tracking system using multiple external markers. Medical physics 33 (11):4073-4084
27. Hoisak JD, Sixel KE, Tirona R, Cheung PC, Pignol J-P (2004) Correlation of lung tumor motion with external surrogate indicators of respiration. International Journal of Radiation Oncology* Biology* Physics 60 (4):1298-1306
28. Fayad H, Pan T, Clement JF, Visvikis D (2011) Technical Note: Correlation of respiratory motion between external patient surface and internal anatomical landmarks. Medical physics 38 (6):3157-3164
29. Zhu G, Yang J, Lu M, Ajlouni M, Kim JH, Yin F (2008) The Investigation on the Location Effect of External Markers in Respiratory Gated Radiotherapy. Journal of Applied Clinical Medical Physics 9 (2)
30. Robert B (2009) Fuzzy and Neural Control DISC Course Lecture Notes. Delft University of Technology: Delft Center for Systems and ControlChawla V (1996) Adaptive network based fuzzy inference system.